ETH zürich

ETH Library

Improving output gap estimation—a bottom-up approach

Working Paper

Author(s):
Rathke, Alexander; Streicher, Sina

Publication date:
2023-11

Permanent link:
https://doi.org/10.3929/ethz-b-000642427

Rights / license:
In Copyright - Non-Commercial Use Permitted

Originally published in:
KOF Working Papers 513

This page was generated automatically upon download from the ETH Zurich Research Collection.
For more information, please consult the Terms of use.

ETH zürich

KOF

KOF Working Papers

Improving output gap estimation—a bottom-up approach

Alexander Rathke, Sina Streicher

No. 513, 11 / 2023

Improving output gap estimation—a bottom-up approach

Alexander Rathke* and Sina Streicher**

November 9, 2023

Abstract

We propose a multivariate Bayesian state space model to identify potential growth and the output gap consistent with the dynamics of the underlying production sectors of the economy and those of inflation and the labor market. Our approach allows us to decompose economic fluctuations and long-term trend growth of output and employment into its driving factors. Applying our model to the Swiss economy reveals substantial divergence among the considered production sectors–their contributions to gap and potential vary both in size and direction. Potential growth has been declining over the past two decades and the data points to labor market frictions and a well-identified Phillips curve. In a comprehensive real-time study, we review revision and forecasting properties of our estimate and compare it to established methods. Overall, we document several advantages of our sector gap model: a) It facilitates the interpretability of economic trends and cycles, allowing for more efficient policy actions, b) it has favorable revision properties compared to standard univariate filtering techniques and a baseline model without sectors, c) it is useful in forecasting output growth and inflation, and d) it produces economically meaningful potential growth rates.

JEL classification: C11, C32, C51, E23, E24, E32, R11.
Keywords: Bayesian state space model, business cycle measurement, Gibbs sampling, output gap, potential output, production sectors

*KOF Swiss Economic Institute, ETH Zurich, Leonhardstrasse 21, 8092 Zurich, Switzerland. Email: rathke@kof.ethz.ch.

**KOF Swiss Economic Institute, ETH Zurich, Leonhardstrasse 21, 8092 Zurich, Switzerland. Email: streicher@kof.ethz.ch.

1 Introduction

Potential output and its difference to actual observed gross domestic product (GDP)—the output gap—are used to determine the cyclical position of the economy. Potential output measures the level of a sustainable and non-inflationary economy, while the output gap reveals short-term deviations from this level (Hall and Taylor, 1991). A positive output gap indicates that the economy is overheating, while a negative gap signals underutilization of production factors. In this paper, we present a model that enables the estimation of potential output and the output gap consistent with the cyclical fluctuations and secular trend dynamics of the sub-sectors of the economy.

For fiscal and monetary policy makers, the output gap serves as a basis for monitoring inflation developments and structural imbalances (Gerlach and Smets, 1999, Coibion and Gorodnichenko, 2015). Generally, most structural models used in macroeconomic forecasting require an estimate of potential output which is key in determining the development of prices and wages (Dupasquier et al., 1999). Central banks rely on a precise estimation of the business cycle to determine possible inflationary and disinflationary pressures. To help maintain a balanced budget, many countries have introduced expenditure caps based on the cyclical position of the economy.[1] Moreover, the aftermath of the Global Financial Crisis has revived the debate on secular stagnation and structural changes in potential growth (Summers, 2015, Gordon, 2014), emphasizing the importance of a reliable and informative estimation strategy.

Potential growth and the output gap are unobservable quantities for which a multitude of estimation procedures have been proposed in the literature. The first category of methods comprises univariate filtering techniques which are essentially free of an economic model and decompose output into a permanent and transitory component (Hodrick and Prescott, 1997, Baxter and King, 1999, Hamilton, 2018, Quast and Wolters, 2022). The

[1]For instance, the fiscal surveillance framework of the European Union uses an estimate of the output gap to extract the structural budget balance. To stabilize the business cycle, spending is increased during economic downturns, while savings are increased in times of economic boom.

next class of methods extends the univariate filters to include other observable variables—such as inflation and unemployment—that are related to the output gap using economic theory (e.g. Kuttner, 1994, Gerlach and Smets, 1999, Blagrave et al., 2015).[2] An alternative multivariate approach builds on the identification of temporary versus permanent shocks using structural vector autoregressions (Cochrane, 1994, Dupasquier et al., 1999), following the contribution of Blanchard and Quah (1989). More recently, Jarociński and Lenza (2018) use six indicators of real economic activity alongside a Phillips curve specification to identify the euro area business cycle. Hasenzagl et al. (2022) propose a semi-structural model that links inflation dynamics and expectations to output, energy prices, and labor market developments. The third class comprises production-function approaches which first decompose output into its production factors—labor, capital, and productivity—and in turn determine their trends and cycles using similar unobserved component models as above (e.g. Havik et al., 2014, Streicher, 2022).

Apart from the unobservability and thus dependence on model assumptions, output gap estimates suffer from significant revisions, particularly at the end of the sample (Orphanides and van Norden, 2002). For some models, the revisions are as large as the output gap itself, which makes them partially useless from the perspective of policy makers. The debate about the reliability of output gap estimates gave rise, for example, to the Hamilton filter (Hamilton, 2018) and a modified version thereof (Quast and Wolters, 2022), which show significantly better real-time properties than other simple univariate statistical trend-cycle decompositions, but which still lack economic theory. Model combinations have been shown to dampen the impact of data revisions and in turn improve real-time output gap estimates (Guérin et al., 2015).

We also aim to benefit from an expanded pool of information by incorporating data on sub-sectors of the economy. Output gaps are usually estimated at the national and supra-

[2]Kuttner (1994) links deviations from potential output to inflation via a Phillips curve relationship and Gerlach and Smets (1999) additionally incorporate the real interest rate through an aggregate demand equation. The model of Blagrave et al. (2015) comprises inflation and labor market developments as well as growth and inflation expectations to inform the output gap.

regional level, i.e., for an economic area or monetary union. Business cycles of individual economic sectors within one such area are rarely considered. However, tracking them separately allows for more targeted and thus efficient policy actions, thereby reducing the chance of pro-cyclical outcomes. For instance, the contraction at the outbreak of the COVID-19 pandemic in 2020 varied widely across different industries and was far from being akin to former economic crisis. Industries associated with leisure activities such as restaurant visits and holiday travel were the hardest hit, while financial and business services experienced a comparably small decline.[3]

We propose a multidimensional state space model which estimates the aggregate output gap and long-term growth consistent with the dynamics of the various sectors of the economy. This approach enables the decomposition of the business cycle into sector contributions on the one hand, and the separation of the sector cycles into economy-wide and sector-specific contributions on the other hand. Our model connects output to employment and unemployment via Okun's law and captures inflation dynamics via a Phillips curve relationship. The structure of the model is inspired by the semistructural models of Jarociński and Lenza (2018) and Hasenzagl et al. (2022). While those authors also use sub components of the economy to inform the business cycle, our model offers a comprehensive and complete overview of the emergence of output and employment fluctuations and secular trends. Its primary innovation is the integration of consistent trends and cycles by imposing aggregation constraints. The resulting decompositions provide a valuable tool to tackle these cycles at their roots, but also to understand the historical developments of potential growth.

We illustrate our sector gap (SG) model for the Swiss economy and document the anatomy of the various driving forces of the up- and downturns since 1991. Our results suggest that the dynamics of the sectors differ considerably and that their contributions to the aggregate business cycle may vary in size as well as direction. Our potential growth

[3] A similar argument can be made for estimates of potential output. Decomposing potential growth into contributions by different economic areas can shed light on why recent trend growth rates lag behind those of earlier decades.

decomposition shows that the sector trade, transport and hospitality is responsible for the slowly decreasing potential growth rate over the past 20 years, with manufacturing counteracting this development. A comparison to output gap figures published by other national institutions reveals at least three considerable distinctions. Our model points to a stronger underutilization during the 1990s, greater overheating of the economy prior to the financial crisis, and a faster recovery afterwards. Most importantly, potential growth in our model is much smoother, highlighting its resilience against transitory shocks and its ability to reflect structural development (Coibion et al., 2017). We show that it is precisely the inclusion of sub-sector information that is responsible for achieving this.

Second, we conduct a comprehensive pseudo real-time evaluation regarding real-time reliability and predictive power for output growth and inflation.[4] A comparison to a baseline specification without sub-sectors and four well-established univariate filters shows that the additional sub-sectors decrease output gap revisions and stabilize trend growth rates.[5] While the SG is more informative in forecasting output growth than univariate filters, it performs equally well than its baseline specification, i.e., its forecasting accuracy is not altered by including additional information on sector output and employment. Similarly, using a standard Phillips curve forecasting equation, we find evidence that our output gap is superior to univariate methods and even adds informational content compared to a benchmark forecasting specification without gap.

Overall, we find that our sector gap model elevates the interpretability of economic trends and cycles, produces smooth potential growth rates in line with theoretical concepts, has favorable pseudo real-time properties and is useful in forecasting inflation and output growth.

This paper is organized as follows. Section 2 details the methodology and in Section 3 we illustrate the application of our model to the Swiss economy. Section 4 provides a

[4]Our analysis focuses on purely filter induced revisions, since actual real-time data on sector output and employment has undergone substantial changes in classification during this period.

[5]Only the Hamilton filter shows better real-time characteristics for the output gap. However, the lack of economic interpretability of its potential growth estimates makes its use impracticable.

comprehensive pseudo real-time analysis and compares revisions and output and inflation forecasting performance across different model specifications and well-known alternative models. The last section concludes.

2 Methodology

This section discusses the intuition and structure of our empirical approach. We estimate a multivariate state space model to extract output gaps for the aggregate economy and its sectors simultaneously. We assume that each sector gap is a linear combination of the common cycle—the output gap—and a sector specific cycle. The sector specific cycles are independent, as are all trend processes. The unemployment and employment gap are each connected to the output gap via Okun's law (Okun, 1963). In the spirit of Stock and Watson (2007), Cogley et al. (2010) and Hasenzagl et al. (2022), among others, we incorporate long-term trend inflation and assume a Phillips curve relationship between short-term inflation developments and output fluctuations.

2.1 Econometric model

We use an unobserved component model to estimate the output gap. The observed variables, i.e., aggregate and sector output and employment, the unemployment rate, and inflation are each linked to unobserved cycles and trend series.

Let y_t denote log output and y_{it} log output in sector i. We assume log output splits into a trend τ_t and a cycle component g_t—the output gap—i.e.,

$$y_t = \tau_t + g_t \tag{1}$$

with local linear trend

$$\begin{aligned} \tau_t &= \tau_{t-1} + \mu_{t-1} + \varepsilon_{\tau t}, \quad && \varepsilon_{\tau t} \sim \mathcal{N}\left(0, \sigma_\tau^2\right), \\ \mu_t &= \mu_{t-1} + \varepsilon_{\mu t}, && \varepsilon_{\mu t} \sim \mathcal{N}\left(0, \sigma_\mu^2\right). \end{aligned} \tag{2}$$

The trend drift μ_t can be interpreted as slowly changing potential growth rate. Shocks to the trend τ_t allow for short-term changes in potential growth. Analogously, we assume that output in each sector i can be separated into a trend τ_{it} and a cycle g_{it}. Each sector cycle is assumed to be linearly connected to the output gap and an idiosyncratic cycle, i.e.,

$$y_{it} = \tau_{it} + g_{it} = \tau_{it} + \beta_i g_t + c_{it}.$$

This implies that the sign of the coefficient β_i determines the nature of the correlation among the cycles.[6] All output sector trends are modeled as in Equation (2) with normal and independent errors

$$\boldsymbol{\varepsilon}_{\tau t} = \left(\varepsilon_{\tau_t}, \varepsilon_{\tau_1 t}, \ldots, \varepsilon_{\tau_n t}\right)', \quad \boldsymbol{\varepsilon}_{\mu t} = \left(\varepsilon_{\mu_t}, \varepsilon_{\mu_1 t}, \ldots, \varepsilon_{\mu_n t}\right)'.$$

To summarize, output in all sectors fluctuates around a longer-term trend whose average growth rate may slowly change over time, driven, for instance, by technological innovation, globalization, or demographic change.

We use both labor market and price developments to inform the fluctuations of the business cycle. The output gap is connected to employment as well as unemployment via Okun's law and to inflation via a Phillips curve relationship. Let e_t denote log employment, u_t the unemployment rate and π_t the inflation rate. We assume

$$\begin{aligned} e_t &= \tau_{et} + \Psi_e\left(L\right) g_t + c_{et}, \\ u_t &= \tau_{ut} + \Psi_u\left(L\right) g_t + c_{ut}, \\ \pi_t &= \tau_{\pi t} + \Psi_\pi\left(L\right) g_t + c_{\pi t} \end{aligned} \tag{3}$$

with $\Psi_\cdot\left(x\right) = \psi_{\cdot 0} + \ldots + \psi_{\cdot k} x^k$. The slack in the economy affects employment, unemployment and inflation both contemporaneously and with a lag of up to k quarters, capturing labor market frictions and price stickiness (e.g. Hasenzagl et al., 2022). In addition, we use Okun's law to help extract the sector output cycles. Since the unemployment rate is usually not available for individual economic sectors, we use sector employment e_{it}. We

[6] Note that $\text{cov}\left(g_t, g_{it}\right) = \text{cov}\left(g_t, \beta_i g_t + c_{it}\right) = \beta_i \,\text{var}\left(g_t\right)$ and $\text{cov}\left(g_{jt}, g_{it}\right) = \text{cov}\left(\beta_j g_t + c_{jt}, \beta_i g_t + c_{it}\right) = \beta_j \beta_i \,\text{var}\left(g_t\right)$.

assume

$$e_{it} = \tau_{e_i t} + \Psi_{e_i}(L)\, g_{it} + c_{e_i t} \tag{4}$$

for $i = 1, \ldots, m$ with $m \leq n$. The employment and unemployment trends are each modeled as local linear trends, analogous to Equation (2) with normal and uncorrelated trend and drift innovations

$$\boldsymbol{\varepsilon}_{\tau_e t} = \left(\varepsilon_{\tau^e t}, \varepsilon_{\tau^e_1 t}, \ldots, \varepsilon_{\tau^e_n t}\right)', \quad \boldsymbol{\varepsilon}_{\mu_e t} = \left(\varepsilon_{\mu^e t}, \varepsilon_{\mu^e_1 t}, \ldots, \varepsilon_{\mu^e_n t}\right)'$$

and $\varepsilon_{\tau_u t}, \varepsilon_{\mu_u t}$, respectively. In the spirit of Stock and Watson (2007), Cogley et al. (2010), and Hasenzagl et al. (2022), trend inflation behaves like a random walk without drift, i.e.,

$$\tau_{\pi t} = \tau_{\pi t-1} + \varepsilon_{\tau_\pi t}, \quad \varepsilon_{\tau_\pi t} \sim \mathcal{N}\left(0, \sigma^2_{\tau_\pi}\right).$$

Collecting all trend and drift innovations, we have that

$$\begin{aligned}
\boldsymbol{\varepsilon}_{\tau t} &= \left(\boldsymbol{\varepsilon}'_{\tau t}, \boldsymbol{\varepsilon}'_{\tau_e t}, \varepsilon_{\tau_u t}, \varepsilon_{\tau_\pi t}\right)' \sim \mathcal{N}\left(0, \boldsymbol{\Sigma}_\tau\right), \\
\boldsymbol{\varepsilon}_{\mu t} &= \left(\boldsymbol{\varepsilon}'_{\mu t}, \boldsymbol{\varepsilon}'_{\mu_e t}, \varepsilon_{\mu_u t}\right)' \sim \mathcal{N}\left(0, \boldsymbol{\Sigma}_\mu\right),
\end{aligned}$$

where $\boldsymbol{\Sigma}_\tau$ and $\boldsymbol{\Sigma}_\mu$ are diagonal. The output gap and all idiosyncratic cycles are modeled as stationary autoregressive processes, i.e., for $\mathbf{c}_t = (g_t, c_{1t}, \ldots, c_{nt}, c_{e_t}, c_{e_1 t}, \ldots, c_{e_n t}, c_{ut}, c_{\pi t})'$, we have that

$$\begin{aligned}
&\boldsymbol{\Phi}(L)\, \mathbf{c}_t = \boldsymbol{\varepsilon}_{ct}, \\
&\qquad \boldsymbol{\varepsilon}_{ct} = \left(\varepsilon_{gt}, \varepsilon_{c_1 t}, \ldots, \varepsilon_{c_n t}, \varepsilon_{c^e t}, \varepsilon_{c^e_1 t}, \ldots, \varepsilon_{c^e_n t}, \varepsilon_{c_u t}, \varepsilon_{c_\pi t}\right)' \sim \mathcal{N}\left(0, \boldsymbol{\Sigma}_c\right),
\end{aligned}$$

with $\boldsymbol{\Sigma}_c$ diagonal, and the lag polynomial $\boldsymbol{\Phi}(x) = 1 - \boldsymbol{\Phi}_1 x - \ldots - \boldsymbol{\Phi}_p x^p$ with diagonal coefficient matrices $\boldsymbol{\Phi}_j, j = 1\ldots, p$.

Some restrictions on the innovation correlations between trends, drifts, and cycles are necessary for identification. The model in Equations (1) and (2) with an autoregressive output gap g_t is identical to the one put forward by Clark (1987). In this model, identification can be achieved by placing restrictions on the innovation covariance structure and by including at least 2 autoregressive lags in the cycle equation (Clark, 1987, Schleicher et al., 2003, Morley et al., 2003, Morley, 2007).[7] We therefore set $p = 2$ and impose that all innovations $\varepsilon_{\tau t}, \varepsilon_{\mu t}$ and ε_{ct} are mutually independent. This implies that transitional changes in consumption or government expenditures do not affect output trend growth. Similarly, demographic or technological changes are assumed to trigger changes in long-run trend growth but not temporary changes in demand.[8] The same identification restrictions carry over to our full model, as each of our additional observation equations features its own trend and cycle component.

2.2 Aggregation and constraints

To ensure that aggregate outcomes are consistent with sector specific ones, we impose linear constraints on the trends and drifts, both for output and employment.[9] Let Y_{it} and Y_{it}^{nom} denote real and nominal output in sector i and let $P_{it} = 100 \; {}^{Y_{it}^{nom}}/_{Y_{it}}$ be the corresponding price index. The associated aggregate series are given by Y_t, Y_t^{nom} and P_t. Real aggregate output is defined as the chain-linked volume index

$$Y_t = \sum_{i=1}^{n} \frac{P_{it-1}}{P_{t-1}} Y_{it} = \sum_{i=1}^{n} w_{ti}^{p} Y_{it},$$

which implies that

$$\begin{aligned} \frac{Y_t}{Y_{t-1}} &= \sum_{i=1}^{n} \frac{P_{it-1}}{P_{t-1}Y_{t-1}} Y_{it-1} = \sum_{i=1}^{n} \frac{P_{it-1}Y_{it-1}}{P_{t-1}Y_{t-1}} \frac{Y_{it}}{Y_{it-1}} \\ &= \sum_{i=1}^{n} \frac{Y_{it-1}^{nom}}{Y_{t-1}^{nom}} \left(\frac{Y_{it}}{Y_{it-1}} \right) = \sum_{i=1}^{n} w_{it}^{nom} \left(\frac{Y_{it}}{Y_{it-1}} \right) \end{aligned}$$

[7] To see this, the model can be rearranged into a reduced form for which there exists an equivalent ARIMA representation which is just identified for $p = 2$ (Hamilton, 1994, Morley et al., 2003, Oh et al., 2006). Intuitively, increasing the autoregressive order p increases the number of non-zero autocovariance terms used to estimate the variances.

[8] Even though the presence of correlation between permanent and transitory shocks cannot be ruled out, it will likely be negligible. See, for instance, Clark (1987), Morley et al. (2003), Morley (2007), and Oh et al. (2006) for an analysis and discussion of unobserved component models with correlated trend, drift, and cycle innovations.

[9] This is technically only relevant if the sectoral series included in the model are exhaustive, i.e., they add up to aggregate output and employment, respectively. Yet, even if they are non-exhaustive, an approximate solution is available by first computing a residual and in turn including a smoothed residual weight on a constant in the constraint equation.

and where w_{ti}^p denotes relative previous period prices and w_{it}^{nom} nominal output weights at $t-1$. Since $\sum_{i=1}^n w_{it}^{nom} = 1$ for all $t \in \mathbb{Z}$, it holds that

$$\frac{Y_t}{Y_{t-1}} - 1 = \sum_{i=1}^{n} w_{it}^{nom} \left(\frac{Y_{it}}{Y_{it-1}} - 1 \right).$$

The growth rate of output can thus be represented as a weighted average of the growth rates of individual sectors, i.e.,

$$\Delta y_t = \sum_{i=1}^{n} w_{it}^{nom} \Delta y_{it},$$

where $y_t = \ln Y_t$.[10] Consequently, assuming that the relative previous period prices w_{it}^p are the same for output and potential, for potential growth, we have that

$$\Delta \tau_t = \sum_{i=1}^{n} w_{it}^{nom} \Delta \tau_{it}, \tag{5}$$

which can be imposed by adding an identity series to the observation equation (Doran, 1992).[11] To ensure that short-term as well as longer-term changes to potential output are consistent, we further set

$$\mu_t = \sum_{i=1}^{n} w_{it}^{nom} \mu_{it}. \tag{6}$$

If short-term changes to trend growth are eliminated, i.e., $\Delta\tau_t = \mu_t$ and $\Delta\tau_{it} = \mu_{it}$ by setting $\varepsilon_{\tau_t} = 0$ and $\varepsilon_{\tau_i t} = 0$, consistency can be attained by only enforcing Equation (6).

For aggregate employment E_t, we have that $E_t = \sum_{i=1}^m E_{it}$, where E_{it} represents the number of persons employed in sector i. Similarly to above, we can deduce

$$\Delta e_t = \sum_{i=1}^{m} w_{it}^{e} \Delta e_{it},$$
$$\mu_{et} = \sum_{i=1}^{m} w_{it}^{e} \mu_{e_i t},$$

where $e_t = \ln E_t$ and $w_{ti}^e = {}^{E_{it-1}}/_{E_{t-1}}$ denotes the share of employment in sector i at point in time $t-1$.

[10]When the data is compiled using the Annual Overlap method, this holds with equality for annual values. For quarterly quantities there can be small deviations, but we assume that these are zero for the trend component we are interested in.

[11]To that end, lagged values of τ_t, τ_{it} need to be included in the state equation.

2.3 State space representation

We stack all observation variables and their cycles, trends, and trend drifts in corresponding order, i.e.,

$$
\begin{aligned}
\underset{\ell\times 1}{\mathbf{y_t}} &= \left(y_t, \mathbf{y}_t^{1:n\prime}, e_t, \mathbf{e}_t^{1:m\prime}, u_t, \pi_t\right)' = (y_1, y_{1t}, \ldots, y_{nt}, e_t, e_{1t}, \ldots, e_{mt}, u_t, \pi_t)' \\
\underset{\ell\times 1}{\mathbf{c}_t} &= \left(g_t, \mathbf{c}_{yt}', c_{et}, \mathbf{c}_{et}', c_{ut}, c_{\pi t}\right)' = (g_t, c_{1t}, \ldots, c_{nt}, c_{et}, c_{e_1 t}, \ldots, c_{e_m t}, c_{ut}, c_{\pi t})' \\
\underset{\ell\times 1}{\boldsymbol{\tau}_t} &= \left(\tau_t, \boldsymbol{\tau}_{yt}', \tau_{et}, \boldsymbol{\tau}_{et}', \tau_{ut}, \tau_{\pi t}\right)' = (\tau_t, \tau_{1t}, \ldots, \tau_{nt}, \tau_{et}, \tau_{e_1 t}, \ldots, \tau_{e_m t}, \tau_{ut}, \tau_{\pi t})', \\
\underset{\ell-1\times 1}{\boldsymbol{\mu}_t} &= \left(\mu_t, \boldsymbol{\mu}_{yt}', \mu_{et}, \boldsymbol{\mu}_{et}', \mu_{ut}\right)' = (\mu_t, \mu_{1t}, \ldots, \mu_{nt}, \mu_{et}, \mu_{e_1 t}, \ldots, \mu_{e_m t}, \mu_{ut})',
\end{aligned}
$$

where $\ell = n + m + 4$ is the number of observables. The state vector can be defined by

$$
\underset{5\ell-1\times 1}{\boldsymbol{\alpha}_t} = \left(\mathbf{c}_t', \mathbf{c}_{t-1}', \mathbf{c}_{t-2}', \boldsymbol{\tau}_t', \boldsymbol{\mu}_t'\right)',
$$

and the measurement and state equations are given by

$$
\begin{aligned}
\underset{\ell\times 1}{\mathbf{y}_t} &= \underset{\ell\times 5\ell-1}{\mathbf{Z}_t}\ \underset{5\ell-1\times 1}{\boldsymbol{\alpha}_t}, \\
\underset{5\ell-1\times 1}{\boldsymbol{\alpha}_t} &= \underset{5\ell-1\times 5\ell-1}{\mathbf{T}_t}\ \underset{5\ell-1\times 1}{\boldsymbol{\alpha}_{t-1}} + \underset{5\ell-1\times 3\ell-1}{\mathbf{R}_t}\ \underset{3\ell-1\times 1}{\varepsilon_t}, \qquad \underset{3\ell-1\times 1}{\varepsilon_t} \sim \mathcal{N}\left(0, \underset{3\ell-1\times 3\ell-1}{\mathbf{Q}_t}\right).
\end{aligned}
\tag{7}
$$

For ease of readibility, we split the system matrices into three blocks, one concerning the vector of contemporaneous and lagged cycles $\left(\mathbf{c}_t', \mathbf{c}_{t-1}', \mathbf{c}_{t-2}'\right)'$, one for the trends $\boldsymbol{\tau}_t$ and a final block for the drifts $\boldsymbol{\mu}_t$. The structure of the blocks is indicated by vertical and horizontal lines. The system matrices of the state space model in Equation (7) are given by

$$
\underset{\ell\times 5\ell-1}{\mathbf{Z}_t} = \left[\begin{array}{ccc|c|c} \underset{\ell\times\ell}{\mathbf{Z}_t^0} & \underset{\ell\times\ell}{\mathbf{Z}_t^1} & \underset{\ell\times\ell}{\mathbf{Z}_t^2} & \mathbf{I}_\ell & \mathbf{0} \end{array}\right], \qquad
\underset{5\ell-1\times 5\ell-1}{\mathbf{T}_t} = \left[\begin{array}{ccc|c|c}
\boldsymbol{\Phi}_1 & \boldsymbol{\Phi}_2 & \mathbf{0} & & \\
\mathbf{I}_\ell & \mathbf{0} & \mathbf{0} & & \\
\mathbf{0} & \mathbf{I}_\ell & \mathbf{0} & & \\
\hline
 & & & \mathbf{I}_\ell & \begin{array}{c}\mathbf{I}_{\ell-1} \\ \mathbf{0}\end{array} \\
\hline
 & & & & \mathbf{I}_{\ell-1}
\end{array}\right],
$$

$$
\underset{5\ell-1\times 3\ell-1}{\mathbf{R}_t} = \left[\begin{array}{ccc} \mathbf{I}_\ell & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \hline \mathbf{0} & \mathbf{I}_\ell & \mathbf{0} \\ \hline \mathbf{0} & \mathbf{0} & \mathbf{I}_{\ell-1} \end{array}\right], \qquad \underset{3\ell-1\times 3\ell-1}{\mathbf{Q}_t} = \left[\begin{array}{ccc} \boldsymbol{\Sigma}_\mathbf{c} & & \\ \hline & \boldsymbol{\Sigma}_\tau & \\ \hline & & \boldsymbol{\Sigma}_\mu \end{array}\right].
$$

The state matrix $\mathbf{T}_t$ contains the autoregressive coefficients $\boldsymbol{\Phi}_j, j \in \{1,2\}$ of the cycles, defines the trend processes as integrated or regular random walks, and additionally includes a number of identities for the lagged cycles. The matrix $\mathbf{R}_t$ connects each state equation to its corresponding innovation term (or none) and the variance-covariance matrix $\mathbf{Q}_t$ contains all cycle, trend and drift variances on its diagonal. The submatrices in $\mathbf{Z}_t$ are defined by

$$
\underset{\ell\times\ell}{\mathbf{Z}_t^0} = \begin{bmatrix} 0 & & & & & \\ \boldsymbol{\beta} & \ddots & & & & \\ 0 & \mathbf{0} & \ddots & & & \\ \vdots & & \ddots & \ddots & & \\ \vdots & & & \mathbf{0} & \ddots & \\ 0 & \cdots & \cdots & \mathbf{0} & 0 & 0 \end{bmatrix} + \mathbf{I}_\ell + \underset{\ell\times\ell}{\tilde{\mathbf{Z}}_t^0}
$$

$$
\underset{\ell\times\ell}{\tilde{\mathbf{Z}}_t^j} = \begin{bmatrix} 0 & & & & & \\ \mathbf{0} & \ddots & & & & \\ \psi_{ej} & \mathbf{0} & \ddots & & & \\ \boldsymbol{\beta}\circ\boldsymbol{\psi}_{e^{1:m}j} & \boldsymbol{\Psi}_{e^{1:m}j} & \mathbf{0} & \ddots & & \\ \psi_{uj} & \mathbf{0} & \cdots & \mathbf{0} & \ddots & \\ \psi_{\pi j} & \mathbf{0} & \cdots & \mathbf{0} & 0 & 0 \end{bmatrix}
$$

and $\mathbf{Z}_t^j = \tilde{\mathbf{Z}}_t^j$ for $j \in \{1,2\}$, where $\boldsymbol{\psi}_{e^{1:m}j} = (\psi_{e_1 j}, \ldots, \psi_{e_m j})$ and $\boldsymbol{\Psi}_{e^{1:m}j} = \operatorname{diag}(\boldsymbol{\psi}_{e^{1:m}j})$ for $j \in \{0,1,2\}$ and $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_n)'$.

The auxiliary matrices $\tilde{\mathbf{Z}}_t^j, j \in \{0,1,2\}$ contain the (lagged) loading of employment ψ_{ej}, sector employment $\boldsymbol{\beta}\circ\boldsymbol{\psi}_{e^{1:m}j}$, unemployment ψ_{uj}, and inflation $\psi_{\pi j}$ on the business cycle and in the case of sector employment on the sector output cycles ($\boldsymbol{\Psi}_{e^{1:m}j}$). In addition, the matrix $\mathbf{Z}_t^0$ links each observable with its contemporaneous cycle and it contains the loading coefficients of sector output on the output gap $\boldsymbol{\beta}$.

To impose constraints on the trends of sector output and employment as discussed in

Section 2.2, the system in Equation (7) needs to be adjusted. In the simple case where shocks to trend growth are set to zero, the aggregation constraints can be imposed by expanding $\mathbf{Z}_t$ and $\mathbf{y}_t$ (Doran, 1992). To be precise, we define

$$\hat{\mathbf{y}}_t = (\mathbf{y}_t', 0, 0)', \qquad \underset{\ell+2\times 5\ell-1}{\hat{\mathbf{Z}}_t} = \left[\begin{array}{ccc|c|c} \underset{\ell\times\ell}{\mathbf{Z}_t^0} & \underset{\ell\times\ell}{\mathbf{Z}_t^1} & \underset{\ell\times\ell}{\mathbf{Z}_t^2} & \mathbf{I}_\ell & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \underset{2\times\ell-1}{\mathbf{Z}_t^\mu} \end{array}\right],$$

$$\underset{2\times\ell-1}{\mathbf{Z}_t^\mu} = \begin{bmatrix} -1 & w_{1t}^{nom} & \dots & w_{nt}^{nom} & 0 & & \cdots & 0 \\ 0 & & \cdots & 0 & -1 & w_{1t}^e & \cdots & w_{mt}^e & 0 \end{bmatrix}.$$

Note that the weights $w_{it}^{nom}, i = 1, \dots, n$ and $w_{jt}^e, j = 1, \dots m$ as defined in Section 2.2 are time-dependent.

If we allow for shocks to trend growth, the system matrices need to be extended further. By adding lagged output and employment trends to the state equation, the additional constraints can again be imposed via Z_t. Let now

$$\hat{\boldsymbol{\alpha}}_t = \left(\boldsymbol{\alpha}_t', \boldsymbol{\tau}_{t-1}'\right)', \qquad \underset{6\ell-1\times 6\ell-1}{\hat{\mathbf{T}}_t} = \left[\begin{array}{ccc|c|c|c} \boldsymbol{\Phi}_1 & \boldsymbol{\Phi}_2 & \mathbf{0} & & & \\ \mathbf{I}_\ell & \mathbf{0} & \mathbf{0} & & & \\ \mathbf{0} & \mathbf{I}_\ell & \mathbf{0} & & & \\ \hline & & & \mathbf{I}_\ell & \mathbf{I}_{\ell-1} & \\ & & & & \mathbf{0} & \\ \hline & & & & \mathbf{I}_{\ell-1} & \\ \hline & & & \mathbf{I}_\ell & & \mathbf{0} \end{array}\right],$$

$$\hat{\mathbf{y}}_t = (\mathbf{y}_t', \mathbf{0})', \qquad \underset{\ell+4\times 6\ell-1}{\hat{\mathbf{Z}}_t} = \left[\begin{array}{ccc|c|c|c} \underset{\ell\times\ell}{\mathbf{Z}_t^0} & \underset{\ell\times\ell}{\mathbf{Z}_t^1} & \underset{\ell\times\ell}{\mathbf{Z}_t^2} & \mathbf{I}_\ell & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \underset{2\times\ell-1}{\mathbf{Z}_t^\mu} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \underset{2\times\ell}{\mathbf{Z}_t^\tau} & \mathbf{0} & -\underset{2\times\ell}{\mathbf{Z}_t^\tau} \end{array}\right],$$

$$\underset{2\times\ell}{\mathbf{Z}_t^\tau} = \begin{bmatrix} -1 & w_{1t}^{nom} & \dots & w_{nt}^{nom} & 0 & & \cdots & \mathbf{0} \\ 0 & & \cdots & 0 & -1 & w_{1t}^e & \cdots & w_{mt}^e & \mathbf{0} \end{bmatrix}.$$

2.4 Estimation

The computational task comprises estimating the unobserved states $\boldsymbol{\alpha}_t$ and the parameters $\boldsymbol{\beta}, \boldsymbol{\psi}_e, \boldsymbol{\psi}_u, \boldsymbol{\psi}_\pi, \boldsymbol{\psi}_{e^{1:m}0}, \boldsymbol{\psi}_{e^{1:m}1}, \boldsymbol{\psi}_{e^{1:m}2}, \boldsymbol{\Phi}_1, \boldsymbol{\Phi}_2, \boldsymbol{\Sigma}_c, \boldsymbol{\Sigma}_\tau, \boldsymbol{\Sigma}_\mu$, where $\boldsymbol{\psi}_e = (\psi_{e0}, \psi_{e1}, \psi_{e2})'$, $\boldsymbol{\psi}_u = (\psi_{u0}, \psi_{u1}, \psi_{u2})', \boldsymbol{\psi}_\pi = (\psi_{\pi 0}, \psi_{\pi 1}, \psi_{\pi 2})'$. Our estimation procedure involves a Gibbs algorithm structured in multiple blocks. The first block draws from the posterior distributions of all trend and trend drift equations. The second block handles all equations involving loading factors and their respective cycles. The third block draws the parameters of the output gap equation. The final block updates the unobserved states conditional on the previously drawn parameters using the simulation smoother of Durbin and Koopman (2012). To compute each posterior we generate 50'000 draws, discard the first 50% and finally consider each 10th draw to limit possible autocorrelation between draws. See Appendix A.2 for details.

We adopt weakly informative priors in the form of diffuse normal or inverse-gamma priors, see Table 1. To facilitate the estimation of meaningful trends and cycles, we use a smoothing parameter $\lambda = \mathbb{E}[\sigma_c^2]/\mathbb{E}[\sigma_k^2], k \in \{\tau, \mu\}$ defining the ratio between the variance of cycle and trend innovations.

Table 1. Prior distributions

Name	Support	Density	Parameters	
β_i	$\mathbb{R}$	Normal	$\mu = 0,$	$\sigma^2 = 1000$
$(\psi_0, \psi_1, \psi_2)'$	$\mathbb{R}^3$	Normal	$\mu = (0,0,0)',$	$\sigma^2 = 1000\mathbf{I}_3$
$(\phi_1, \phi_2)'$	$\mathbb{R}^2 \times I_{\phi \in S_\phi}$	Normal	$\mu = (0,0)',$	$\sigma^2 = 1000\mathbf{I}_2$
σ_c^2	$(0, \infty)$	Inverse-gamma	$\nu = 6,$	$s = 4$
σ_μ^2	$(0, \infty)$	Inverse-gamma	$\nu = 6,$	$s = 4\lambda^{-1}$
σ_τ^2	$(0, \infty)$	Inverse-gamma	$\nu = 6,$	$s = 4\lambda^{-1}$

Notes: $I_{\phi \in S_\phi}$ denotes the indicator function and S_ϕ the stationary region of an AR(2) process. All indices are suppressed for the sake of readability. The normal distribution is parameterized via mean and variance, the inverse-gamma distribution via degrees of freedom ν and location s with mean $s/\nu-2$. The smoothing constant λ is set to 100 implying an a priori signal-to-noise ratio of 1%.

3 An illustration for Switzerland

We estimate our model with $m = 6$ exhaustive economic production sectors, autoregressive cycles of order $p = 2$, and to capture a potentially lagged reaction of the labor market, we set $k = 2$. We first give an overview of the data and in turn elaborate on the role of the prior distributions in identifying the model. The subsequent section discusses the estimated trends and cycles of the Swiss economy at an aggregate level and then moves to the sector contributions of the output and employment gaps. A similar analysis is done for potential growth and employment trend growth.

3.1 Data

We use quarterly aggregates of gross domestic product for Switzerland according to the production approach. In addition to real GDP, we consider real gross value added before adjustments of five economic sectors. To facilitate the cyclical interpretation of output, we use output series that are adjusted for major international sports events.[12] Aggregate adjustments are treated as an individual sector to complete the model. All production series are provided by the Swiss State Secretariat for Economic Affairs (SECO). The composition of the sectors is documented in Table 2. For employment, we use full-time equivalents gathered by the Swiss Federal Statistical Office (FSO) as part of the Job Statistic (JOBSTAT). The provided sectoral full-time equivalent series can be aggregated such that the resulting series largely correspond to the production ones specified in Table 2.[13,14] Finally, we use the unemployment rate based on the definition of the International Labor Organization (ILO) and for inflation we use the year-on-year growth rate of the Consumer Price Index (CPI). Both series are provided by the Swiss FSO. All series are seasonally-adjusted and all output series are additionally calendar-adjusted.

Figure 1 shows the development of output (solid lines) and full-time equivalent employment (dashed lines) in Switzerland at the aggregate as well as disaggregate level. The economic development of the various sectors differs, in some cases significantly. For

[12] Several international sport organisations are based in Switzerland, including the International Association Football Federation (FIFA), the Union of European Football Associations (UEFA) and the International Olympic Committee (IOC). These associations contribute to output mainly through income from intangible assets such as licenses and patents. However, from a business cycle perspective, the periodicity of their contributions to output disables an economic interpretation. At the same time, output from international sporting events is usually created abroad and therefore only of little relevance to the domestic economy in Switzerland. Excluding output from international sporting events therefore creates a more fitting measure of economic output for business cycle analysis.

[13] For the agricultural sector NOGA 01-03, no employment data is available. However, given the relative size of the sector compared to manufacturing as a whole (less than 1% of output versus 22%), this shortcoming is negligible.

[14] We repeat the analysis in Section 3 for an extended set of sub-sectors and report our findings in Section A.3.1 in the Appendix. The differences between the trends, cycles, and drifts of output, employment, unemployment, and inflation are negligible.

Table 2. Structure of sectors

Sector	Sub-sectors	NOGA
Manufacturing	Agriculture, forestry and fishing	01-03
	Mining and quarrying	05-09
	Manufacturing	10-33
	Electricity, gas, steam and air conditioning supply	35
	Water supply, sewerage, waste management and remediation activities	36-39
Construction	Construction	41-43
Trade, transport and hospitality	Trade, repair of motor vehicles and motorcycles	45-57
	Transportation and storage; Information and communication	49-53; 58-63
	Accommodation and food service activities	55-56
Financial and other economic services	Financial service activities	64
	Insurance service activities	65
	Real estate, professional, scientific and technical activities; Administrative and support service activities	68-57; 77-82
Government and consumer-related services	Public administration and defense; compulsory social services	84
	Education	85
	Human health and social work activities	86-88
	Arts, entertainment and recreation	90-93
	Other service activities	94-96
	Activities of housholds as employers and producers for own use	97-98
Adjustments	Taxes on products	
	Subsidies on products	

Notes: The General Classification of Economic Activities (NOGA) provided by the Swiss FSO is derived from the Statistical Classification of Economic Activities in the European Union (NACE). The current NOGA (2008) was enacted in 2008.

instance, the construction sector experienced a considerable decline in the 1990s, after the bursting of a housing bubble while the overall economic development was decent. Sectors also react differently to crises such as the 2007–2008 financial crisis or the COVID-19 pandemic that began in early 2020. The financial crisis mainly affected manufacturing and financial and other economic services, while consumer-related services did not experience a decline. The coronavirus pandemic initially led to a reduction in output across all sectors, but this decrease was particularly pronounced in trade, transport and hospitality. In general, roughly since the second half of the 1990s, all sectors have been on a steady growth path.

The development of full-time equivalent employment is also heterogeneous across sectors. Approximately until the turn of the century, employment has been decreasing in manufacturing, construction and trade, transport, and hospitality. Most sectors show an upward trend thereafter, while employment in manufacturing has been stagnant. For the aggregate economy and most sectors, there exists a positive correlation between output and employment with the exception of manufacturing which is experiencing elevated levels of productivity growth.

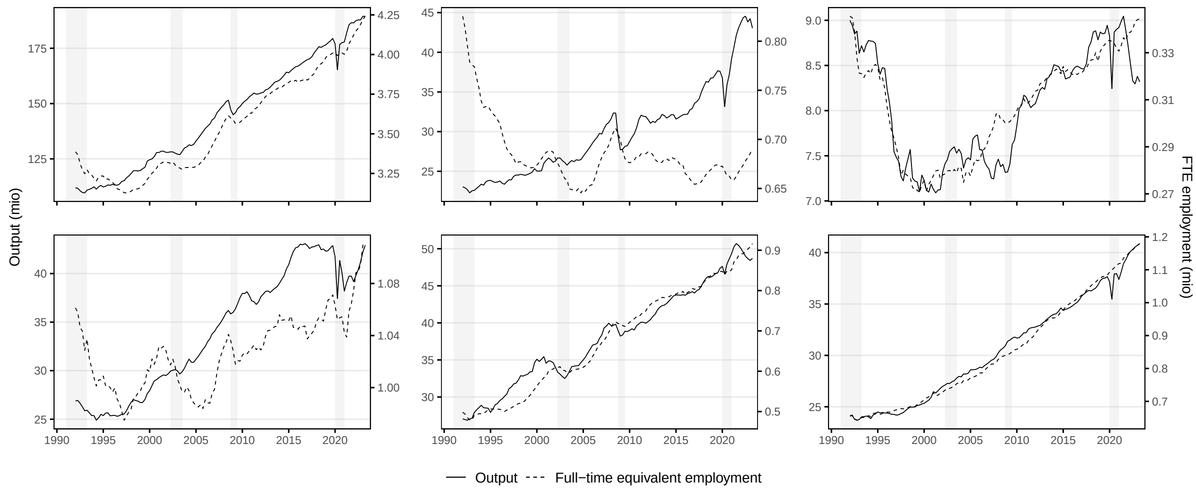


Figure 1: Output and full-time equivalent employment in different sectors. The series are depicted from 1992 Q1 until 2023 Q2. The solid lines (left axes) show quarterly output in million 2020 CHF and the dashed lines (right axes) depict full-time equivalent (FTE) employment in million. Vertical shaded areas highlight recessions.

3.2 Prior and posterior distributions

Figure 2 illustrates prior and posterior densities for all parameters that load on the business cycle.[15] The posteriors are well peaked indicating that the data is quite informative in estimating the model parameters.

All sector cycles are positively correlated with the output gap, as indicated by the posterior means of the loading factors. As expected, the posterior of the loadings of aggregate employment on the output cycle has positive mean. The contemporaneous effect appears to be the strongest and it wears off with increasing lag order. Accordingly, the posterior distribution of the loadings of the unemployment gap on the output gap and its lags has negative mean. The Phillips curve appears well-identified—the positive connection of inflation and the business cycle is evident and similar to above, it slowly decreases in size with increasing lag order.

[15] Table A.2 in Appendix A.5 summarizes the mean, median, first and ninth decile of the posterior distribution of all parameters.

Prior and posterior distributions for the loading factors of sector employment on the respective output series and lags thereof are shown in Figure A.2 and for the cycle, trend, and drift variances in Figure A.3 in Appendix A.4. The posteriors indicate a positive contemporaneous relationship between sector employment and sector output. The model also suggests that the lagged reaction of employment is heterogeneous among the considered production sectors.

(a) Sector output loadings on aggregate output

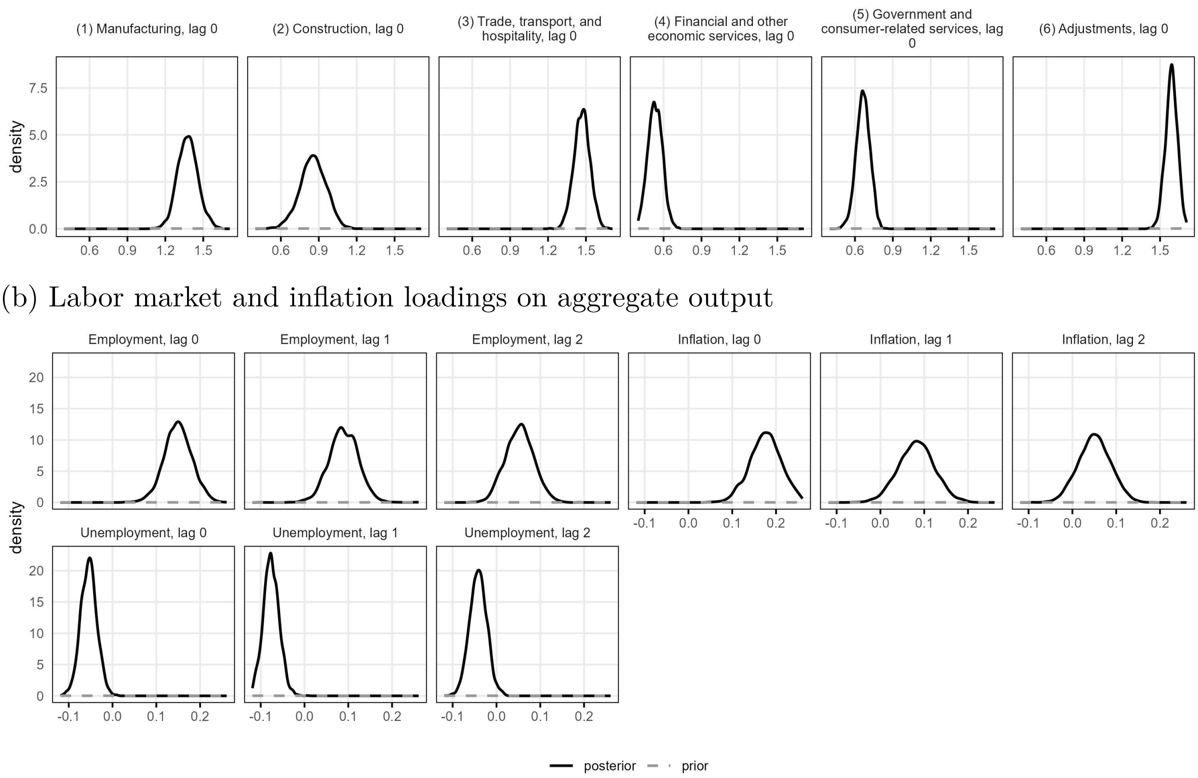


Figure 2: Prior and posterior distributions. The prior distributions are specified as in Table 1. BS denotes the business cycle (output gap). The posterior densities are based on 50’000 draws, with the first 25’000 being discarded. Of the remaining draws, all but every 10th draw are discarded.

3.3 Aggregate trends and cycles in the Swiss economy

Figure 3 plots aggregate output and employment, the unemployment rate and inflation alongside their trend estimates (panel (a)) and corresponding cycles (panel (b)) with 68% highest-posterior density intervals (HPDI). We can clearly recognize the stylized facts of the Swiss business cycle. Despite comparably low trend growth rates, the nineties were marked by a long phase of underutilization, naming it Switzerland's lost decade. The next recession took place after the dot-com bubble. Leading up to Global Financial Crisis in 2007–2008, our model clearly emphasizes an overheating of the economy. Interestingly, the subsequent Great Recession was much less pronounced than the ones before it. During the 2010s, the aggregate Swiss economy was mostly operating close to capacity. The most severe underutilization combined with an unusually swift recovery occurred at the outset of the COVID-19 pandemic.

The labor market shares much of the same dynamics. As expected, there is an inverse relation between the output gap and the unemployment gap, while its correlation to the employment gap is evidently positive. Underutilization of economic production factors mostly came hand in hand with elevated levels of unemployment and a negative employment gap and vice versa. At the beginning of the pandemic, however, the labor market response was less pronounced than indicated by the historic relationship to the output gap, suggesting that the massive use of short time working schemes successfully protected the labor market. For instance, the responses of the employment and unemployment gaps in the second quarter of 2020 were roughly 12% respective 43% below the responses in line with historic declines in capacity utilization, i.e., the idiosyncratic parts of the labor market gaps counteract the effect of the negative shocks to the output gap.[16]

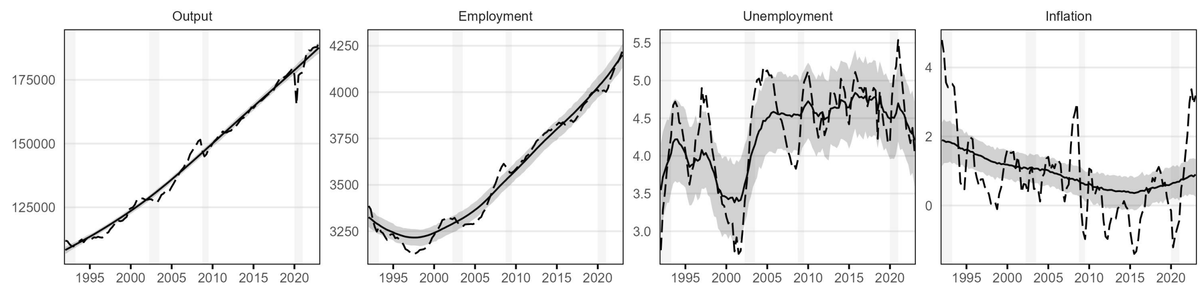
In line with the continuous population growth in Switzerland, particularly since the turn of the millennium, employment alongside its trend have been steadily increasing. Trend unemployment has experienced a level shift between 2000 and 2007, and has remained relatively stable at rates between 4.5% and 5%. Only lately has trend unemploy-

[16]The figures are based on the medians of the posterior distributions.

ment been decreasing again, reflecting the tight situation on the labor market.

The long-term inflation trend has been slowly decreasing from around 1.9% in 1992 to levels between 0.4% to 0.5% during the European debt crisis. Roughly since 2020, trend inflation started to increase slightly to rates close to 0.8%. We identify three phases marked by a positive inflation gap: First, the surge in inflation in the early 1990s was triggered by a spillover from the reunification boom in Germany.[17] The second phase occurred before the Great Recession, when the Swiss Franc experienced an unusually long period of weakness and the third phase in 2022, triggered by the war in Ukraine and post COVID-19 pandemic effects. Negative inflation gaps have occurred in times of strong appreciation of the Swiss Franc, e.g., after the SNB scrapped the floor of CHF 1.20 to the Euro in January 2015 and in the course of the demand shortfall during the pandemic.

(a) Trends



(b) Gaps (in %)

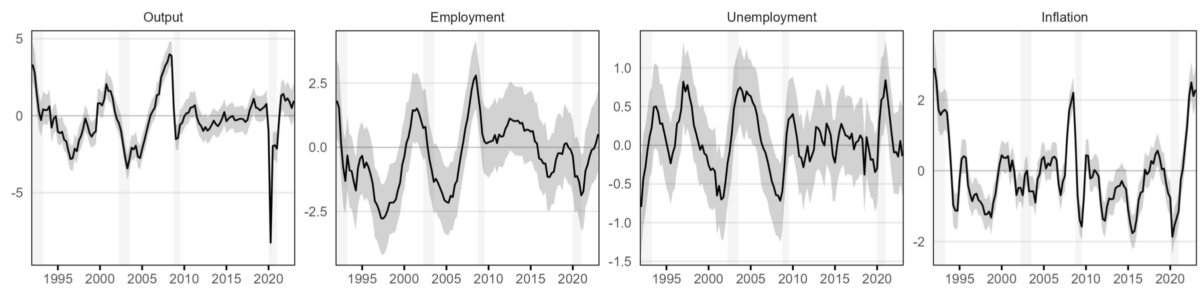


Figure 3: Aggregate trends and gaps. The original data are dashed and the trends solid (upper panel). The estimated gaps are solid (lower panel). The shaded areas indicate 68% HPDI. Vertical shaded areas highlight recessions.

---

[17]For more details on this episode, see Rich (1997).

3.4 A sector perspective on output and employment cycles

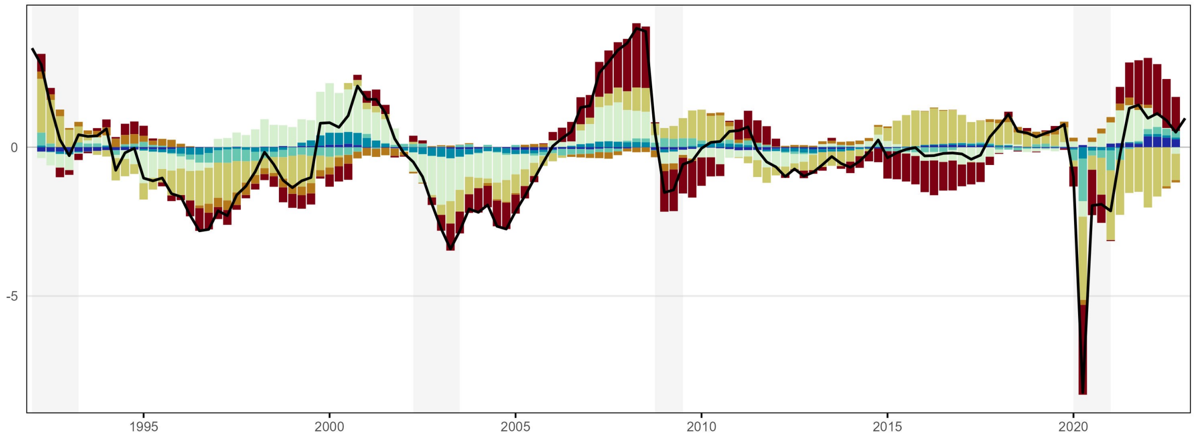
The output and employment gaps are decomposed into sectoral contributions in Figure 4. In the lost decade, a broad mix of sectors contributed to the negative output gap. The dot-com recession is mainly attributable to financial services, which enjoyed strong growth before the crisis. The overheating prior to the Financial Crisis is mostly related to manufacturing, trade, transport and hospitality, and financial and other economic services. However, the negative contributions in the aftermath are limited. Even though there was a strong consolidation in the banking sector after the crisis, its negative contribution were somewhat offset by a sizable compensatory expansion in the insurance sector. Moreover, while the manufacturing sector suffered, wholesale trade and especially merchanting activities acted as a stabilizer. A similar picture emerges after the SNB lifted the floor for the euro in January 2015: While there were negative contribution from manufacturing and business related sectors, trading activities stabilized the aggregate output gap. When the COVID crisis hit, all sectors were initially affected by the partial lockdown of activities and other containment restrictions. In fact, also personal and government related services contribute to the negative output gap, a sector that normally exhibits no business cycle at all. While the manufacturing sector recovered rapidly, the consumer-oriented services experienced a prolonged period of slowdown. The advantage of such a comprehensive decomposition is obvious: Policy targeting the aggregate output gap is likely to overlook the state of the individual sectors, resulting in a loss in efficacy.

By construction, the picture for employment is similar to the one for value added, but the importance of the underlying sector contributions differs. The three aggregate sectors manufacturing, trade, transport, and hospitality, and financial and other economic services show the largest contributions to the employment gap, whereas those of the remaining sectors, i.e., the construction sector and government and consumer-related services are comparably small. Hence, intuitively, government employment does not react as strongly to the business cycle as other sectors do.[18]

[18]See Figure 5 for a decomposition of sector employment cycles into contributions by the (lagged) business

When comparing the output and employment gaps, it is particularly noteworthy that although the impact of the appreciation of the Swiss Franc in 2015 on output was limited, it is very well reflected in the employment gap. The slowdown in output, which was driven by manufacturing and financial and other economic services was counteracted by an expansion in merchanting activities. However, this expansion was not transmitted to the labor market, resulting in a negative employment gap.

(a) Output gap decomposition



(b) Employment gap decomposition

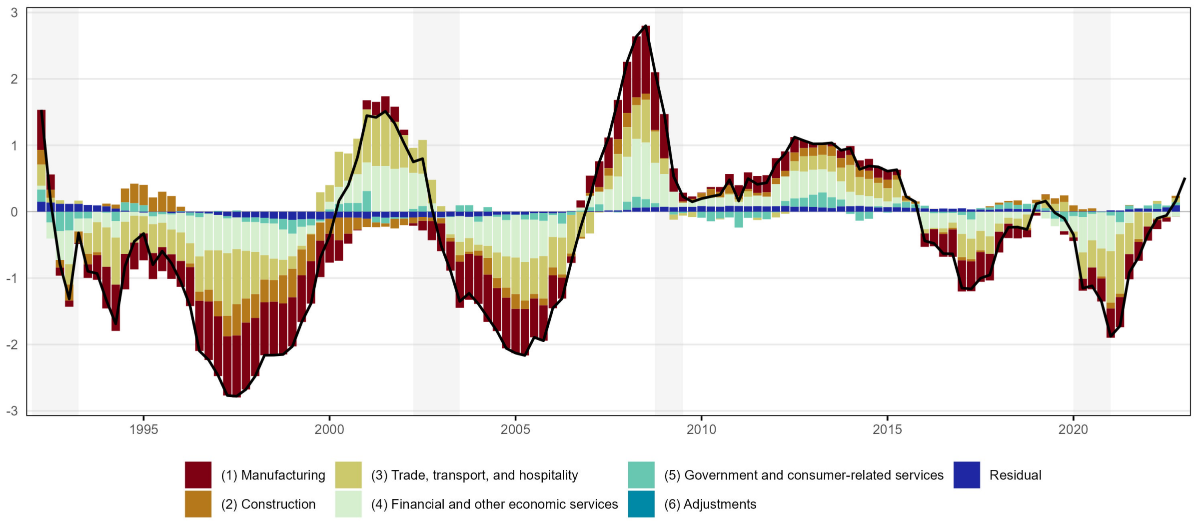


Figure 4: Output and employment gap decomposition. Contributions to the output and employment gap are in %. Vertical shaded areas highlight recessions.

The breakdown of the individual output and employment gaps in Figure 5 reveals that despite some commonalities, there is also plenty of room for idiosyncrasies among the sectors. Panel (a) contains the cycle decomposition for sector output and panel

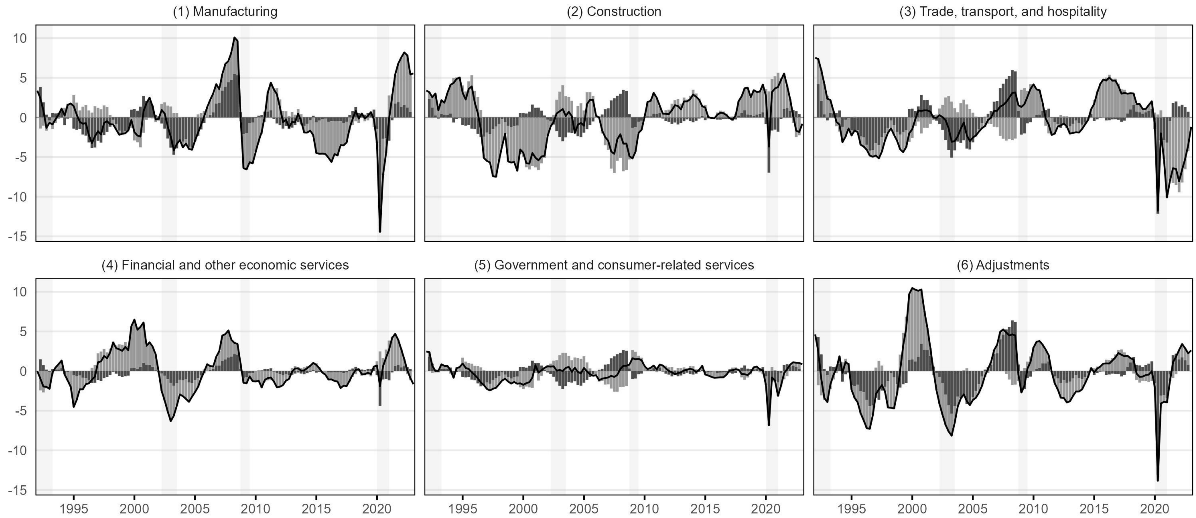
cycle and idiosyncratic employment cycles.

(b) that of sector employment. Panel (c) shows similar decompositions for employment, unemployment and inflation. Light areas represent sector-specific output and employment contributions. For sector output, aggregate employment, unemployment, and inflation, dark areas show the contribution of the common business cycle. For sector employment, they signal the influence of the sector-specific business cycle.

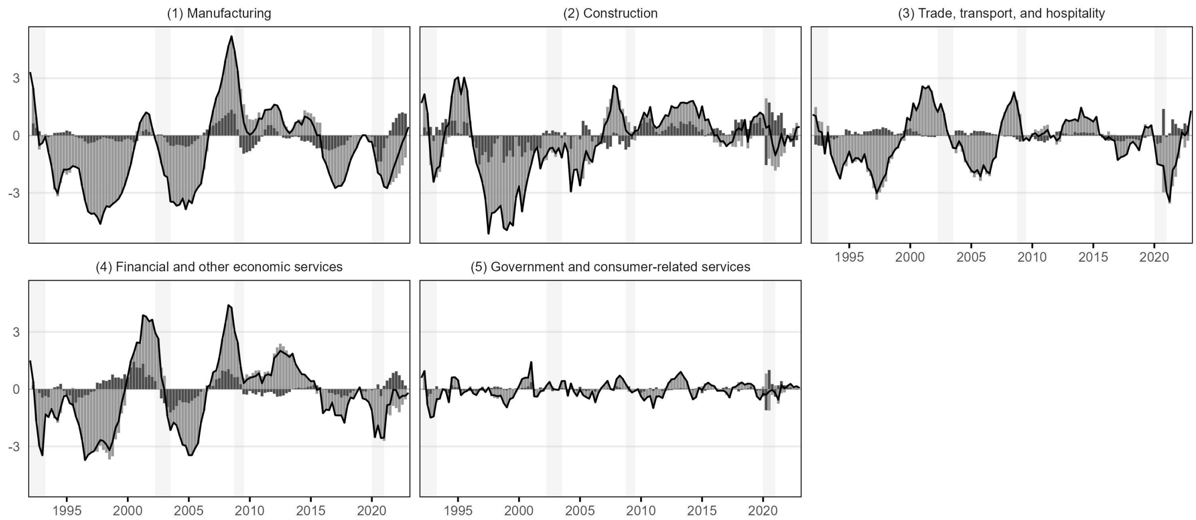
The sector output gaps are heterogeneous, not only in terms of their progression and amplitude but also in terms of how they are impacted by the aggregate business cycle. As suggested by the posterior distributions in Figure 2, the output gap has the strongest influence on manufacturing and on the collected sector trade, transport and hospitality. In contrast, for the sector employment gaps, idiosyncratic factors predominate the impact of sector output fluctuations. It is worth noting that the output cycle of financial and other economic services appears to be less sensitive than its employment cycle. Compared to most other sectors and in contrast to the output cycle, the employment gap contains periods of strong under- and overutilization, indicating the sectors' ability to cushion economic fluctuations. Okun's law is nicely reflected in the employment and particularly in the unemployment gap decomposition, and also the Phillips curve relationship is clearly visible. Much of the idiosyncratic part of the inflation gap can be attributed to oil price fluctuations and movements in the exchange rate.

Table A.1 in Appendix A.5 presents the correlation coefficients between the business cycle, sector output gaps, employment, unemployment and inflation gaps, and those between sector output and its associated sector employment. The direction and magnitude of the correlation figures confirm our previous results. As expected, the unemployment gap is negatively correlated with the output gap, most sector gaps, and the inflation gap. Interestingly, correlation between the output gap and the construction gap is near zero, which can be attributed to the fact that in times of low international demand, emigration to Switzerland increases, which in turn increases the demand for housing.

(a) Sector output gap decomposition



(b) Sector employment gap decomposition



(c) Aggregate gap decomposition

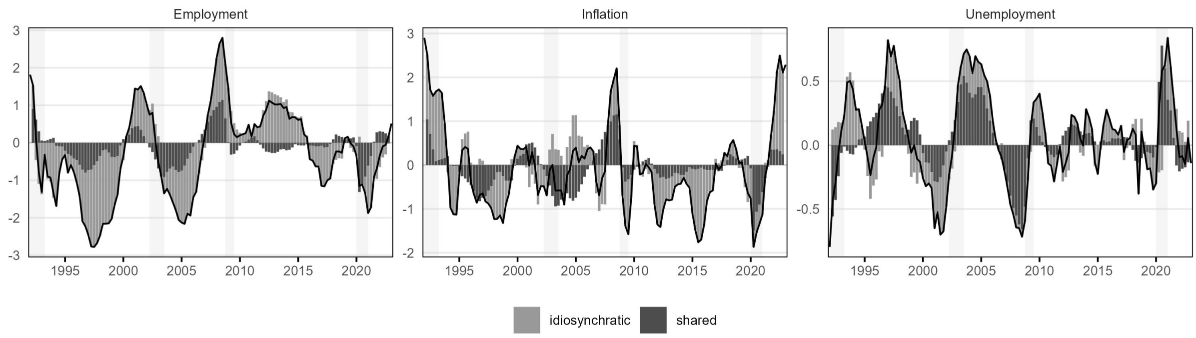


Figure 5: Gap decompositions. All gaps are in %. Light shaded areas represent idiosyncratic contributions and dark areas those of the respective loading series. Vertical shaded areas highlight recessions.

3.5 A sector perspective on potential growth and trend employment

Figure 6 shows the decomposition of structural potential growth (upper panel) and that of the employment drift (lower panel).[19] Quarterly potential output growth has increased from 0.40% in the early nineties to peak levels of approximately 0.50% from 2004 until 2009 and in turn decreased back to roughly 0.40% in 2022.[20] More recently, the decline has been driven by the sector trade, transport and hospitality, while the increasing contribution of manufacturing has counteracted this development. In 2020, the manufacturing sector surpassed a quarterly trend growth rate of 0.8%, making it the sector with the highest growth potential. This reflects the sector's changing composition, with the highly productive pharmaceutical sector becoming increasingly important.

In contrast, the breakdown of trend employment growth reveals a continued shift toward a service-based economy, driven by labor-intensive sectors such as health care and education (panel (b) in Figure 6). Trend employment growth in manufacturing and construction is no longer as negative as it was in the 1990s, but it is now stagnating. This development also reflects the shift to higher productivity activities in these sectors. Again, employment trends reflect developments in the international economy, the exchange rate, and emigration to Switzerland.

3.6 Comparison to models from policy institutions

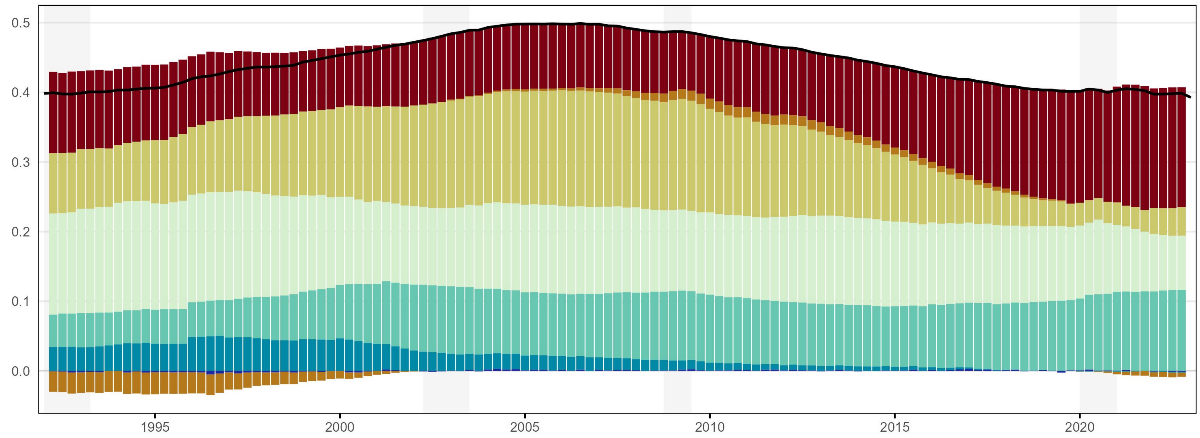
We compare our measure of the business cycle and trend growth to alternative models in Figure 7. The output gaps published by the Swiss National Bank (SNB), the Swiss State Secretariat of Economic Affairs (SECO) and the KOF Swiss Economic Institute are each based on a production function approach.[21] Finally, we also include a baseline version of

[19] Sector trends and drifts alongside credible sets can be found in Figures A.4 and A.5 in Appendix A.4.

[20] These quarterly rates corresponds to annual rates of approximately 1.6%, 2.0%, and 1.6%, respectively.

[21] A Cobb-Douglas production function is used to split potential output into three input factors: non-financial capital stock, trend labor input and the trend of total factor productivity. Total factor productivity contains the component of output that cannot be explained by the production factors capital and labor. See e.g. Havik et al. (2014) and Streicher (2022) for details on the methodology.

(a) Output drift decomposition



(b) Employment drift decomposition

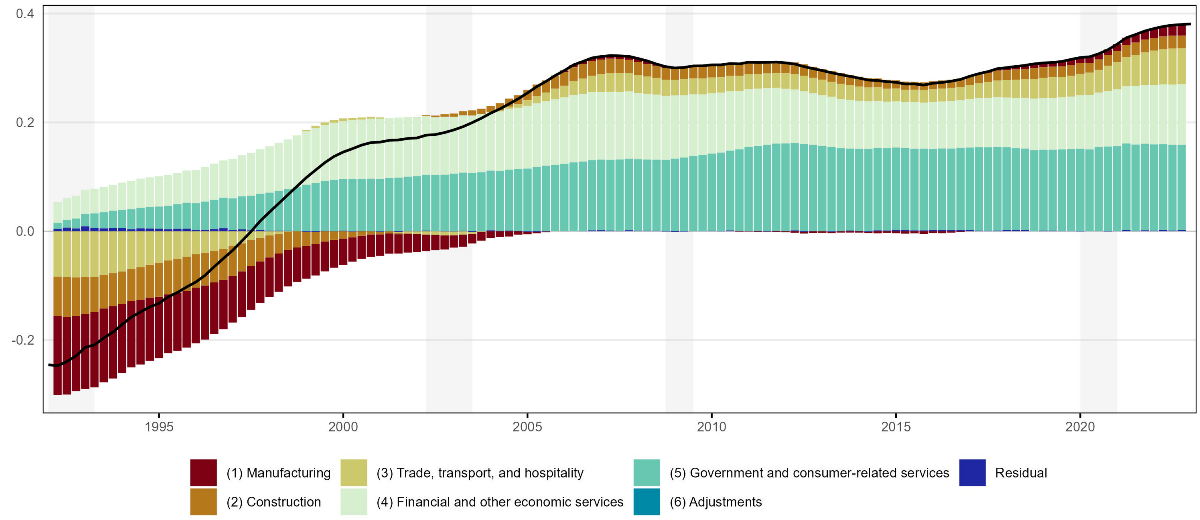


Figure 6: Output and employment long-term trend growth decomposition. Contributions and quarterly growth rates are in %. Vertical shaded areas highlight recessions.

our model excluding all sector output and employment equations (model (5), see Table 3 in Section 4).

All estimates of the output gap suggest a similar course of the business cycle in Switzerland. While our baseline model is broadly in line with all remaining models in terms of the level and variability, the model that includes sectoral output and employment (model (1) SG) shows some divergence. The clearest difference can be observed in two phases. First, our model indicates that the underutilization during the nineties was more pronounced. Second, the boom leading up to the Financial crisis was even more extreme, with the subsequent recession being less prominent and of shorter duration. As we have seen in Figure 4, the latter fact is mostly attributable to a strong performance in the

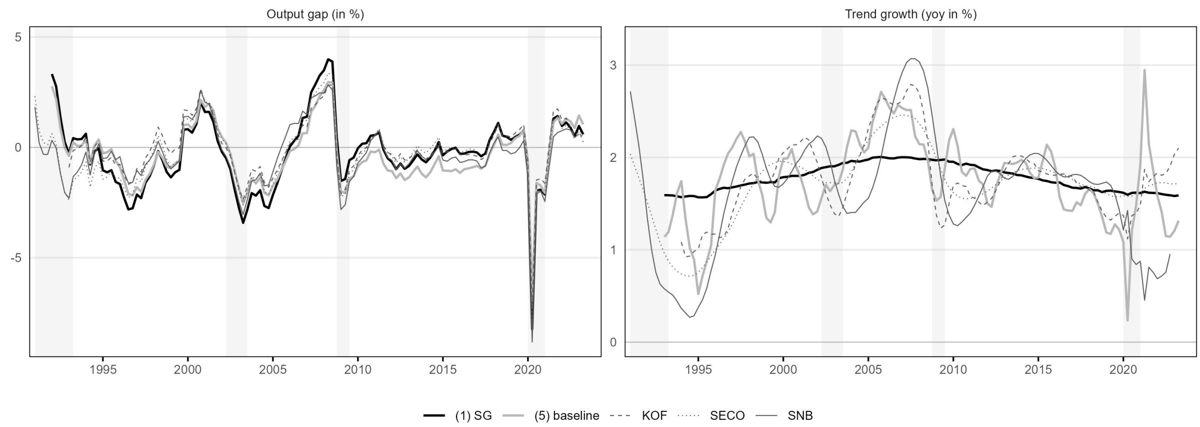


Figure 7: Comparison across policy institutions. Output gaps and annualized trend growth rates in %. The output gaps from SECO, SNB, and KOF are each based on a production-function approach. Vertical shaded areas highlight recessions.

sector trade, transport, and hospitality.

The comparably large amplitude of the output gap in our model can in part be attributed to the rather smooth trend growth rate (right side of Figure 7). The standard deviation of annualized potential growth in model (1) is 0.15% compared to 0.43%, 0.41%, and 0.69% for the KOF, SECO, and SNB models and 0.46% for the baseline model (5). Given mean potential growth rates of $1.7 - 1.8\%$ across models, model (1) seems more plausible from an economic perspective.[22]

Smoother estimates of potential output are desirable for multiple reasons. Potential output is typically understood as the longer-term level of sustainable output, influenced by persistent movements in investment, the labor market, and population growth (Hodrick, 2020, Quast and Wolters, 2022). In addition, fiscal and monetary policy makers benefit from smooth trend estimates to prevent rapid policy changes, which is particularly important given the delays in implementation and enforcement (Quast and Wolters, 2022). Indeed, many estimates of potential output react to transitory shocks (Coibion et al., 2017), rendering them impractical from the perspective of a policy maker. Potential output in our full model including sector output and employment alongside aggregation

[22]The somewhat erratic behaviour of the baseline trend compared to the KOF and SECO trends is due to the fact the latter models do not allow for short-term shocks to total factor productivity and thus to potential output. Instead, all variation stems from shocks to the slowly adjusting growth rate, thereby leading to smoother estimates.

constraints does not suffer from such excess cyclicality, suggesting that it reflects purely structural developments.

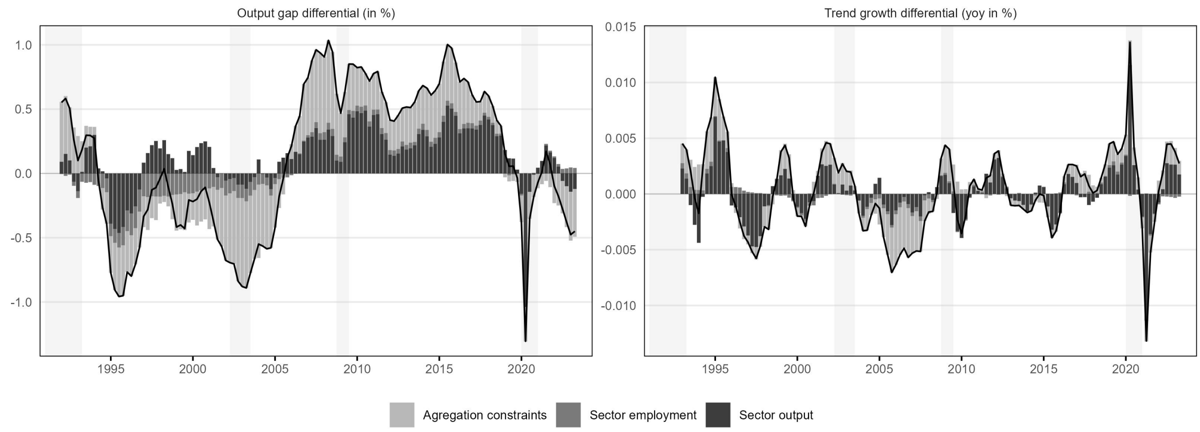


Figure 8: Sources of model differences. The left panel decomposes the differences between the output gap estimates of models (1) and (5) into its contribution by the aggregation constraints, sector output, and sector employment. The right panel decomposes the differences in annualized potential growth rates between the respective models. Vertical shaded areas highlight recessions.

Figure 8 exposes some of the underlying factors between the difference in output gap estimates. We split the differences in output gap and trend growth between models (1) and (5) into contributions by the aggregation constraints, sector output, and sector employment. To arrive at this decomposition, we estimate two complementary models: First, model (1) without sector employment[23], and second, we additionally drop the aggregation constraints. Most of the divergence can be explained by the inclusion of sector output and particularly its corresponding aggregation constraints. The latter make up 58% of the difference in output gap estimates while sector output and sector employment account for 32% and 10%, respectively. For potential output growth, including sector output accounts for 54% of the difference, additionally imposing constraints for 45% and the inclusion of sector employment for 2%.[24]

[23]This corresponds to model (3) in Table 3 in Section 4.

[24]Needless to say, there are multiple ways to decompose the differences between model (1) and the baseline model (5). Using alternative decompositions, the main conclusions remain valid, i.e., the reported shares are similar.

4 Real-time analysis

This section investigates pseudo real-time properties of our model regarding revisions and output and inflation forecasting performance. To that end, we use data published until 2023 Q2 and estimate a variety of models in pseudo real-time, i.e., by cutting off recent data from 2005 Q1 onward and subsequently extending the sample quarter by quarter. As actual real-time data on sector output and employment has undergone substantial changes in classification during this period, we limit our analysis on the impact of purely filter induced revisions.

Our analysis includes four different specifications of our proposed sector gap model (SG), two baseline specifications excluding sectoral information and four well-established univariate filtering techniques. The models are summarized in Table 3. Vintages of the output gap and annualized trend growth rates are shown in Figure A.6 in Appendix A.4. The output gap and potential growth vintages differ in terms of volatility, amplitude, and revisions. The revisions of the HP and BK filter are mostly right sided, i.e., the business cycle towards the beginning of the sample is hardly revised, while the remaining models revise the entire path. Notably, with the exception of the HP filter, most models produce somewhat unreasonable estimates for the vintage at the onset of the COVID-19 pandemic. However, expanding the sample further appears to push estimates back to their prior path. In the following revision and forecasting exercises, we exclude the recent COVID-19 pandemic to avoid outlier distortion and later report robustness checks including this period.[25]

[25] It is highly unlikely that the real-time estimates at the beginning of the pandemic would have been used by policy makers without some adaptation to account for the extreme shock in the first two quarters of 2020.

Table 3. Models

Abbreviation	Model
(1) SG	Full model including sector output and employment
(2) SG w/o trend shock	Model (1) excluding shocks to trends
(3) SG w/o sector empl.	Model (1) excluding sector employment
(4) SG w/o trend shock, w/o sector empl.	Model (1) excluding shocks to trends, sector employment
(5) Baseline	Model (1) excluding sector output and employment
(6) Baseline w/o trend shock	Model (5) excluding shocks to trend
(7) HP	Hodrick-Prescott filter (Hodrick and Prescott, 1997)
(8) BK	Baxter-King filter (Baxter and King, 1999)
(9) Hamilton	Hamilton filter (Hamilton, 1994)
(10) mod. Hamilton	Modified Hamilton filter (Quast and Wolters, 2022)

Notes: Models included in the pseudo real-time analysis. SG denotes sector gap.

4.1 Revisions

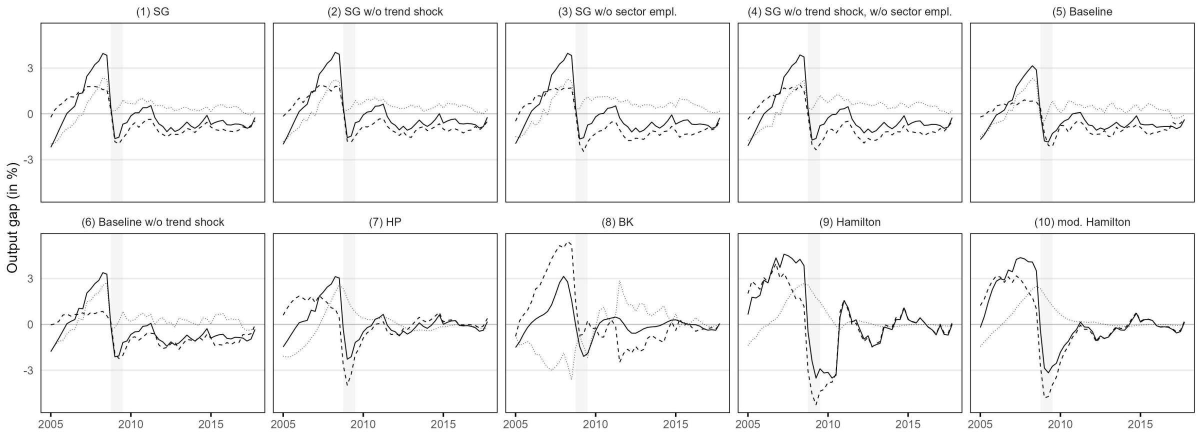
An important property of output gaps is real-time reliability. As filtering methods are prone to large revisions when new information becomes available, output gaps are often revised substantially, limiting its usefulness for monetary and fiscal policy makers (Orphanides and van Norden, 2002).

In our revision analysis, we include all vintages from 2005 Q1 until 2017 Q4 and define 2019 Q4 as the final vintage.[26] Figure 9 shows the final (solid), initial (dashed), and the corresponding revision (dotted) of the output gap estimates (top panel) and its corresponding trends (bottom panel). Unsurprisingly, gap revisions have been the largest prior to the Financial Crisis of 2007–2008, and for all methods but the BK filter, the overheating was underestimated. The corresponding annualized potential growth rates (bottom panel) appear somewhat more heterogeneous. Models (1) – (4) produce stable potential growth with little revisions, while the two baseline models (5) and (6) allow for more variations. Notably, the BK and Hamilton filters produce very volatile trend growth rates, which are hard to justify from an economic point of view. The erratic behaviour is somewhat mitigated for the modified version of the Hamilton filter, yet, its potential growth rate clearly still reflects transitory developments.

Table 4 summarizes revision and reliability indicators of the considered models. We

[26]We implicitly assume that most revisions take place within two years after the initial release, which is standard in the literature (Orphanides and van Norden, 2002, Quast and Wolters, 2022).

(a) Output gap (in %)



(b) Potential growth (yoy in %)

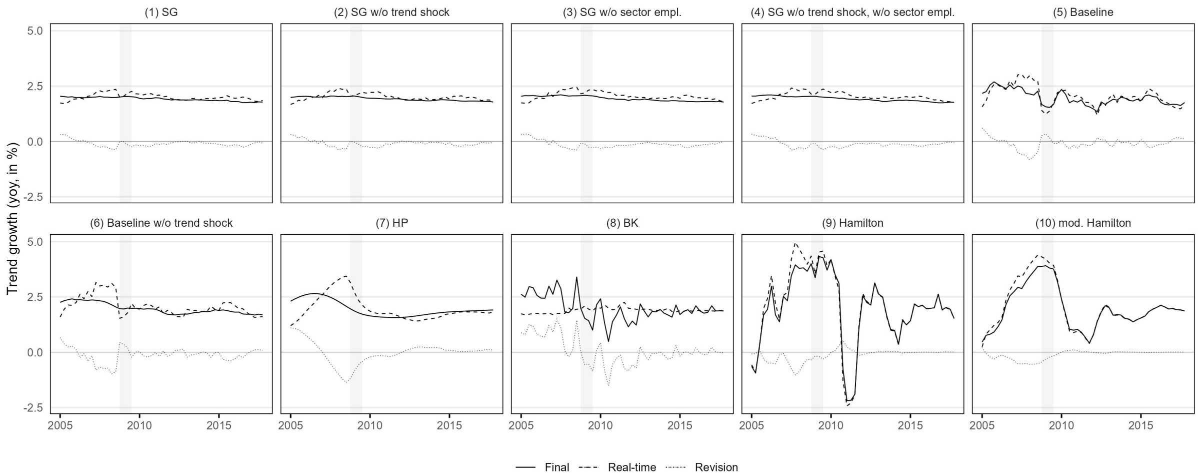


Figure 9: Revisions, pseudo real-time, and final estimates. Pseudo real-time estimates are estimated from vintage 2005 Q1 until 2019 Q4 at quarterly frequency. Vertical shaded areas highlight recessions.

report mean and standard deviation of the final vintage and the revisions, the root mean squared revisions (RMSR), and to account for differences in gap variability, the RMSR normalizes by the standard deviation of the final vintage (NRMSR). Finally, we document the correlation (COR) and the frequency of sign mismatches (SIGN) between initial and final vintage.

Regarding output gap revisions, the first thing to note is that the NRMSR for models (1) and (2) is lower than for those excluding employment (3) and (4) and the two baseline specification (5) and (6). Second, the additional sectoral information of models (1) – (4) increases the correlation to the final vintage. However, the sign conformity of the baseline models is among the lowest across all models. The four competing models (7) – (10)

show mixed results. The variability of the HP filter is similar to that of the final output gap vintage itself and the BK revisions even surpass it. The two Hamilton filters both produces a comparably volatile output gap, yet with a high correlation between initial to final vintage and a sign mismatch of only 4–6%.

The inclusion of sectors also seems to stabilize trend growth rates and their revisions; models (1) – (4) produce the least volatile final trend estimates, least volatile revisions, and smallest RMSR.[27] The ratio between the variance of final quarterly trend growth to the one of the final output gap amounts to roughly 0.1-0.2% for models (1) – (4), 2% and 0.4% for the baseline models (5) and (6) and 1%, 17%, 9%, and 2% for the univariate models.

Table 4. Revision and reliability indicators

	Final vintage		Revision				Initial vs. Final	
	Mean	SD	Mean	SD	RMSR	NRMSR	COR	SIGN
				Output gap (in %)				
(1) SG	−0.28	1.42	0.32	0.83	0.88	0.62	0.81	0.15
(2) SG w/o trend shock	−0.23	1.42	0.40	0.78	0.87	0.62	0.83	0.17
(3) SG w/o sector empl.	−0.16	1.40	0.54	0.79	0.95	0.68	0.83	0.13
(4) SG w/o trend shock, w/o sector empl.	−0.24	1.39	0.47	0.80	0.92	0.66	0.82	0.12
(5) Baseline	−0.25	1.19	0.32	0.75	0.80	0.68	0.77	0.10
(6) Baseline w/o trend shock	−0.26	1.29	0.29	0.84	0.88	0.69	0.76	0.10
(7) HP	0.00	1.07	−0.03	1.02	1.01	0.94	0.61	0.15
(8) BK	−0.06	0.99	−0.35	1.45	1.47	1.48	0.75	0.29
(9) Hamilton	0.00	2.14	0.36	0.93	0.99	0.46	0.91	0.04
(10) mod. Hamilton	0.05	1.89	0.33	0.84	0.90	0.47	0.91	0.06
				Trend growth (yoy in %)				
(1) SG	1.82	0.18	−0.09	0.14	0.17	0.91	0.41	0.00
(2) SG w/o trend shock	1.81	0.19	−0.09	0.15	0.17	0.92	0.46	0.00
(3) SG w/o sector empl.	1.83	0.20	−0.12	0.16	0.20	1.02	0.46	0.00
(4) SG w/o trend shock, w/o sector empl.	1.82	0.21	−0.12	0.16	0.20	0.97	0.41	0.00
(5) Baseline	1.80	0.41	−0.08	0.27	0.28	0.69	0.82	0.00
(6) Baseline w/o trend shock	1.81	0.31	−0.11	0.33	0.35	1.12	0.67	0.00
(7) HP	1.78	0.44	−0.01	0.52	0.52	1.17	0.44	0.00
(8) BK	1.89	0.52	0.08	0.64	0.64	1.23	−0.55	0.00
(9) Hamilton	1.80	1.42	−0.11	0.28	0.30	0.21	0.99	0.00
(10) mod. Hamilton	1.84	0.90	−0.10	0.20	0.22	0.25	0.99	0.00

Notes: RMSR denotes the root mean squared revision and NRMSR the normalized RNSR, i.e., the ratio of RMSR to the standard deviation of the final estimate. COR denotes the correlation and SIGN the frequency of sign mismatches between real-time and final estimates. Pseudo real-time estimates are estimated from 2005 Q1 until 2017 Q4 at quarterly frequency and 2019 Q4 defines the final vintage.

The main findings remain valid when we expand the set of vintages to include the COVID-19 pandemic (see Table A.3 in Appendix A.5). The revisions are elevated across all models and so is the frequency of sign mismatches between initial and final output gap,

[27]For the sake of completeness, we include the NRSMR and COR for trend growth rates in the table, even though their interpretation is not economically meaningful.

which is not surprising given the size of the shock. Interestingly, the two baseline models, the BK filter, and the Hamilton filter show sign mismatches for annualized potential growth, highlighting one of the drawback of volatile trend estimates.

Overall, we find that the output gap and potential growth based on our sector model are to some extend more reliable than their baseline model counterparts and those of the univariate filters considered. Even though the two Hamilton filters show comparably good real-time characteristics, the economic interpretation of potential growth is difficult.

4.2 Forecasting performance: Output

We follow Nelson (2008) and Quast and Wolters (2022) and compare the output growth forecasting performance of the competing models. The intuition is simple, a negative output gap should be indicative of an above average growth in the future, while a positive gap should imply growth rates below trend.

We use the pseudo real-time estimates to predict the h quarter ahead output growth using three specifications, i.e.,

$$y_{t+h} - y_t = c + \tilde{\beta}_h g_t + \varepsilon_{t+h|t}, \tag{8a}$$

$$y_{t+h} - y_t = c + \tilde{\beta}_h g_t + \tilde{\gamma}_h \Delta g_t + \varepsilon_{t+h|t}, \tag{8b}$$

$$y_{t+h} - y_t = c + \sum_{k=0}^{p} \tilde{\beta}_{hk} g_{t-k} + \varepsilon_{t+h|t}, \tag{8c}$$

where y_t denotes log output and g_t is the pseudo real-time output gap estimate. If the coefficient $\tilde{\beta}_h$ in Equation (8a) is negative, the output gap predicts trend-reverting behavior of output growth over the h quarter horizon. The extension in Equation (8b) controls for changes in the level of the gap (Nelson, 2008). In a similar notion, Equation (8c) includes up to $p \leq 12$ lags of the output gap, where p is chosen based on the Bayesian Information Criterion using the final vintage.

We estimate Equations (8a) – (8c) for all models in Table 3 and pseudo real-time vintages from 2005 Q1 until 2019 Q4. With the exception of the two Hamilton filters, the coefficients $\tilde{\beta}_h$ in Equation (8a) are predominantly significantly negative for horizons

$h > 1$, and increasing in absolute terms, indicating the ability of the gap to predict trend-reverting dynamics of output growth (see Table A.4 in Appendix A.5).[28] Table 5 reports the root mean squared errors (RMSE) of model (1) relative to the alternative specifications and other filtering techniques. A value smaller one thus indicates superior forecasting performance of model (1) and statistical significance is tested via a Diebold-Mariano test.[29] Across all three forecasting equations, our model performs equally well as its closely related alternative specifications (2) – (4) and the baseline specifications (5) and (6), i.e., not enabling transitory shocks to trend growth and dropping sectoral output or employment does not alter the forecasting performance. We find evidence that the forecasting performance of the Hodrick-Prescott filter (7) and the Baxter-King filter (8) is inferior to that of model (1).[30] However, the forecast errors of the Hamilton filter (9) and its modified version (10) are not statistically different from those or model (1).

Overall, the results suggest that while the output gap in our model is more informative in forecasting output growth than univariate filters, it's forecasting accuracy does not benefit from the additional information on sector output and employment. If we expand the vintage sample to include the COVID-19 pandemic, the main conclusions are not altered (see Table A.5 in Appendix A.5).

[28]For the two versions of the Hamilton filter, the frequency of statistically significant negative values at the 10% level surpasses 90% only for horizons $h > 8$ and $h > 7$, respectively. At the same time, the coefficients are comparably small, partly reflecting its relatively volatile output gap but also indicating its inferior output forecasting performance.

[29]The null hypothesis states that there are no differences.

[30]The results for Equation (8c) suggest that while model (1) outperforms the HP-filter for one quarter ahead projections, the opposite is true for some medium-term horizons.

Table 5. GDP forecast evaluation: Relative RMSE of model (1) SG to alternative models

	Horizon in quarters											
	1	2	3	4	5	6	7	8	9	10	11	12
	Equation (8a): $p = 0$											
(2) SG w/o trend shock	0.999	1.000	1.001	1.003	1.001	1.000	1.007	1.008	1.007**	1.003	1.004	1.008*
(3) SG w/o sector empl.	1.004	1.000	1.003	1.001	0.995	0.995	0.994	0.989	0.989	0.989	0.983	0.978
(4) SG w/o trend shock, w/o sector empl.	1.006	1.004	1.004	1.004	0.999	0.994	0.994	0.989	0.989	0.986	0.979	0.971
(5) Baseline	1.010*	1.011	1.017	1.028	1.024	1.020	1.027	1.010	1.018	1.026	1.036	1.042
(6) Baseline w/o trend shock	1.002	1.005	1.008	1.014	1.006	1.000	1.004	0.995	1.007	1.021	1.032	1.048
(7) HP	0.920*	0.938*	0.911*	0.883*	0.867*	0.853*	0.835	0.837	0.837	0.834	0.825	0.820
(8) BK	1.007	0.977	0.940	0.891**	0.854	0.834	0.815	0.785	0.741	0.688	0.653	0.632
(9) Hamilton	1.018	1.001	0.996	0.982	0.961	0.944	0.934	0.943	0.965	0.977	0.988	0.979
(10) mod. Hamilton	1.020	0.999	0.988	0.967	0.940	0.922	0.916	0.925	0.942	0.948	0.947	0.929
	Equation (8b): $p = 0$, including Δg_t											
(2) SG w/o trend shock	1.000	1.001	1.003	1.004**	1.004	1.001	1.007	1.008	1.006*	1.003	1.003	1.005**
(3) SG w/o sector empl.	1.004	0.999	1.000	0.998	0.993	0.991	0.990	0.987	0.986	0.987	0.982	0.976
(4) SG w/o trend shock, w/o sector empl.	1.004	1.002	1.002	1.003	0.998	0.993	0.994	0.991	0.991	0.990	0.982	0.972
(5) Baseline	0.987	0.996	1.001	1.008	1.004	1.003	1.007	1.001	1.011	1.023	1.031	1.035
(6) Baseline w/o trend shock	0.989	1.001	1.004	1.008	1.003	0.998	1.002	1.000	1.008	1.023	1.029	1.037
(7) HP	0.941*	0.961*	0.946	0.920	0.904	0.903	0.890	0.890	0.897	0.896	0.884	0.879
(8) BK	0.883	0.869	0.840	0.810	0.787*	0.777**	0.761*	0.748	0.705	0.675	0.649	0.627
(9) Hamilton	0.948	0.991	0.984	0.972	0.958	0.943	0.943	0.956	0.964	0.983	0.988	0.961
(10) mod. Hamilton	0.998	0.986	0.977	0.960	0.941	0.925	0.917	0.927	0.928	0.931	0.931	0.912
	Equation (8c): $p < 12$ chosen by BIC											
(2) SG w/o trend shock	1.000	0.987	0.992	1.019**	0.998	0.995	1.003	1.008	1.010	1.004	0.965	0.969
(3) SG w/o sector empl.	1.004	0.999	0.918	1.019	1.014	1.007	0.995	0.999	0.997	0.993	0.979	0.974
(4) SG w/o trend shock, w/o sector empl.	1.004	1.002	0.924	1.044	1.034	1.019	1.004	1.002	1.001	0.997	0.980	0.968
(5) Baseline	0.987	0.996	0.952	1.071	1.073	1.070	1.065	1.087	1.084	1.055	1.013	0.989
(6) Baseline w/o trend shock	0.989	1.001	1.004	1.048	1.040	1.032	1.028	1.058	1.059	1.040	1.017	0.994
(7) HP	0.941*	0.975	0.974	1.103	1.108	1.110	1.104	1.121***	1.099**	1.058	0.973	0.883
(8) BK	0.698*	0.435***	0.081***	0.107***	0.132**	0.166***	0.109**	0.103*	0.153***	0.133	0.123*	0.124*
(9) Hamilton	0.948	0.991	0.895	1.036	1.032	1.048	1.056	1.105	1.101	1.081	1.065	1.034
(10) mod. Hamilton	0.998	0.971	0.912	1.037	1.039	1.068	1.105	1.165	1.153	1.113	1.037	1.011

Notes: *, **, and *** denote significant differences in forecasting accuracy at the 10, 5, and 1% level based on a two-sided Diebold and Mariano (1995) with squared loss. Pseudo real-time estimates are estimated for vintages from 2005 Q1 until 2019 Q4 at quarterly frequency.

4.3 Forecasting performance: Inflation

We use two autoregressive distributed lag (ADL) Phillips curve specifications to evaluate and compare the ability of the pseudo real-time output gap estimates to forecast inflation (see e.g. Stock and Watson, 1999, Clark and McCracken, 2006, Kamber et al., 2018, Quast and Wolters, 2022). Let P_t denote the quarterly CPI, $\pi_{jt} = \ln P_t - \ln P_{t-j}$ denotes CPI inflation and g_t is the pseudo real-time output gap estimate. We use $j \in \{1, 4\}$ to consider both quarter-on-quarter and year-on-year inflation. The two specifications include contemporaneous and lagged values of the output gap and (change in) inflation, i.e.,

$$\pi_{jt+h} - \pi_{jt} = c + \sum_{k=0}^{p_\pi} \tilde{\gamma}_{kh} \Delta \pi_{jt-k} + \sum_{k=0}^{p_g} \tilde{\delta}_{kh} g_{t-k} + \varepsilon_{t+h|t}, \tag{9a}$$

$$\ln P_{t+h} - \ln P_t = c + \sum_{k=0}^{p_\pi} \tilde{\gamma}_{kh} \Delta \ln P_{t-k} + \sum_{k=0}^{p_g} \tilde{\delta}_{kh} g_{t-k} + \varepsilon_{t+h|t}. \tag{9b}$$

Equation (9a) predicts h quarter ahead inflation π_{jt+h} while Equation (9b) makes projections for the total inflation rate over h quarters, i.e., $\bar{\pi}_{t+h} = \ln P_{t+h} - \ln P_t$.[31] The maximum lag sizes $p_\pi, p_g \in [0, 12]$ are again chosen via the Bayesian Information Criterion based on the final vintage (Quast and Wolters, 2022).

Table 6 shows the root mean squared forecast errors of model (1) relative to the competing models and a specification of Equations (9a) and (9b) without the output gap. We again use the Diebold-Mariano test to check for significant differences in forecasting accuracy of model (1) to the remaining models.

When it comes to forecasting quarterly inflation (Equation 9a), model (1) performs similar to its alternative specifications, i.e., model (2) – (4), as well as its baseline specifications (5) and (6). While there is evidence that model (1) performs better than all competing univariate models, especially for medium and long-term forecast horizons, only for q-o-q inflation it partly outperforms the simple benchmark model without gap. However, projections for total h quarter inflation appear to benefit from adding a measure of economic slack to the forecasting equation. Model (1) outperforms the benchmark model for most horizons while differences to the remaining models are statistically insignificant.[32]

Our results indicate a slight superiority of our model, which is in contrast to recent literature. Stock and Watson (2007, 2008) and Blanchard et al. (2015)—among others—document a decrease in predictability of inflation over past decades. In addition, naive benchmark models have been proven almost impossible to beat (Stock and Watson, 2007, 2008, Dotsey et al., 2017, Kamber et al., 2018, Forbes et al., 2021, Quast and Wolters, 2022). While most of this research focuses on the United States, similar findings have been reported for Switzerland. For instance, Gerlach (2017) finds that the link between

[31] Specification (9a) imposes a unit root in inflation which is in line with our assumption that trend inflation follows a random walk.

[32] Table A.6 in Appendix A.5 reports the results including the COVID-19 pandemic. The main conclusions remain unchanged. Not all that surprising, the benefit of including the output gap in benchmark projections of total h period ahead inflation is less stable for short-horizons, since the pandemic involved a large demand shock unrelated to past economic developments.

inflation and economic slack was lost in the early 1990s and Stuart (2018) documents a reduction of the importance of the output gap starting in 1993. In contrast, Hasenzagl et al. (2022) find a well-identified Phillips curve for the United States, using a medium-size semistructural time series model which also incorporates energy price fluctuations. Similarly, Coibion and Gorodnichenko (2015) stress the importance of oil prices which have lead to an increase in household inflation expectations following the Great Financial Crisis, thereby accounting for the missing disinflation. As suggested by the inflation gap decomposition in Section 3.4, we also find a sizeable cycle in CPI inflation unrelated to the real economy, driven mainly by fluctuations in energy prices and the exchange rate. At the same time, a Phillips curve relationship informative for future inflation developments is supported by the data.

Table 6. Inflation forecast evaluation: Relative RMSE of model (1) SG to alternative models

	Horizon in quarters											
	1	2	3	4	5	6	7	8	9	10	11	12
	Equation (9a): h period ahead y-o-y inflation ($\pi_{t+h} = P_{t+h} - P_{t+h-4}$)											
(2) SG w/o trend shock	0.999	0.998	0.998	0.996	0.996	0.997	0.998	0.960	1.008***	1.010**	1.011	1.009
(3) SG w/o sector empl.	0.999	0.998	0.999	1.002	1.000	0.999	1.000	0.990	0.926	0.994	1.005	1.011
(4) SG w/o trend shock, w/o sector empl.	1.000	1.000	1.001	1.001	0.998	0.997	0.997	0.999	0.932	0.996	0.998	1.006
(5) Baseline	1.011	1.006	1.010	1.015	1.012	1.007	1.005	0.962	0.972	1.161	1.035	0.997
(6) Baseline w/o trend shock	1.001	1.007	1.011	1.016	1.010	1.003	1.000	0.957	0.944	1.007	0.990	0.974
(7) HP	1.005	1.002	0.999	0.996	0.981	0.963**	0.948*	0.897	0.880***	0.993	0.888***	0.832***
(8) BK	1.056	0.983	0.862	0.093***	0.095***	0.061**	0.060*	0.080**	0.073***	0.116***	0.094*	0.076*
(9) Hamilton	1.020	0.998	0.997	1.007	0.798*	0.797	0.881	0.809*	0.836***	0.929	0.777	0.844
(10) mod. Hamilton	1.014	0.970	0.952	0.964	0.918*	0.769*	0.849***	0.106	0.798***	0.909	0.849	0.858
Only infl.	1.004	0.991	0.991	1.018	0.989	0.970	0.963	0.924	0.929	1.062	0.975	0.927
	Equation (9a): h period ahead q-o-q inflation ($\pi_{t+h} = P_{t+h} - P_{t+h-1}$)											
(2) SG w/o trend shock	0.997**	0.999	0.997	1.000	1.000	0.996*	0.997	0.997	0.996	1.003	1.002	1.001
(3) SG w/o sector empl.	0.999	1.001	1.003	1.001	1.002	1.005	1.003	0.997	1.000	1.009	1.010	1.007
(4) SG w/o trend shock, w/o sector empl.	1.000	1.002	1.001	1.000	0.999	0.997	1.000	0.996	1.001	1.005	1.001	1.004
(5) Baseline	1.005	1.010	1.014	1.017	1.009	1.013	1.007	0.983	0.990	1.008	0.997	0.985
(6) Baseline w/o trend shock	1.006	1.010	1.014	1.013	0.998	0.999	1.007	0.986	0.988	1.002	0.991	0.971
(7) HP	0.990	0.997	0.995	0.973	0.959	0.952*	0.932**	0.914**	0.939*	0.925**	0.921**	0.914**
(8) BK	0.993	0.927	0.883	0.851	0.922	0.954	1.014	0.980	1.016	0.981	0.978	0.977
(9) Hamilton	1.013	0.984	0.979	0.944	0.953	0.975	1.027	1.040	1.013	0.972	0.943	0.929
(10) mod. Hamilton	0.954	0.959	0.961	0.948	0.907	0.930	0.983	0.941	0.991	0.982	0.939	0.913
Only infl.	0.992	0.908	0.872	0.965	0.919	0.903**	0.859**	0.877	0.907	0.897***	0.890***	0.843***
	Equation (9b): h period inflation ($\bar{\pi}_{t+h} = \ln P_{t+h} - \ln P_t$)											
(2) SG w/o trend shock	1.001	0.999	0.997	0.997	0.997	0.998	0.999	0.999	0.998	0.999	1.000	1.000
(3) SG w/o sector empl.	1.005*	1.006	1.008	1.011	1.005	1.004	1.002	1.000	0.998	0.997	0.996	0.994
(4) SG w/o trend shock, w/o sector empl.	1.006	1.006	1.007	1.009	1.005	1.004	1.002	0.999	0.997	0.995	0.994	0.992
(5) Baseline	1.001	1.007	1.013	1.014	0.999	0.996	0.998	1.002	1.000	1.000	1.001	1.001
(6) Baseline w/o trend shock	1.007	1.014	1.020	1.021	1.004	1.001	1.001	1.003	0.999	0.998	0.999	0.983***
(7) HP	1.014	1.028	1.028	1.023	1.020	1.018	1.014	1.016	0.974	1.003	0.998	0.983
(8) BK	0.968	0.965	0.969	0.991	0.953	0.945	0.951	0.964	0.931	0.914	0.926	0.934
(9) Hamilton	0.970	1.008	1.040	1.062	0.996	0.975	0.977	0.987	0.954	0.939	0.955	0.963
(10) mod. Hamilton	0.972	1.010	1.043	1.068	1.005	0.985	0.983	0.990	0.956	0.940	0.951	0.956
Only infl.	0.981	0.939**	0.906*	0.873*	0.790*	0.752**	0.736**	0.729**	0.695**	0.681***	0.698***	0.705**

Notes: *, **, and *** denote significant differences in forecasting accuracy at the 10, 5, and 1% level based on a two-sided Diebold and Mariano (1995) with squared loss. Pseudo real-time estimates are estimated for vintages from 2005 Q1 until 2019 Q4 at quarterly frequency.

5 Conclusion

Most conventional multivariate methods estimate the output gap consistent with inflation or unemployment dynamics. We go beyond this approach and propose a multivariate state space model in which potential output and the output gap match the dynamics of the underlying production sectors. The complementary information on sector output and employment allows for a decomposition of economic fluctuations and long-term developments into its driving factors, thereby providing a more profound and useful estimate. Tracking the economic dynamics of individual sectors, rather than the economy as a whole, can increase the efficiency of fiscal and monetary policy actions and avoid procyclical outcomes.

We illustrate the proposed model to document the dynamics of the Swiss economy, revealing substantial divergence among the considered production sectors. Manufacturing and financial and other economic services are the main drivers of the Swiss business cycle, which demonstrates their dependence on fluctuations in the global economy. The slow decline in growth potential over the past 20 years is mainly due to a slowdown in the sector trade, transport and hospitality, while structural shifts in the manufacturing sector toward higher productivity activities have cushioned this development. A comparison of our estimate of the business cycle to those of national institutions reveals some divergences. For instance, our model points to a stronger overheating prior to the Great Financial Crisis and a faster recovery afterwards. Our output gap decomposition exposes that the latter is caused by an expansion in merchanting activities.

In a comprehensive pseudo real-time evaluation, we show that the additional subsector information helps to decrease filter induced revisions of the output gap and stabilizes potential output growth. Only the two Hamilton filters possesses better real-time characteristics, however, considering the erratic behavior of the corresponding trends and thus lack of economic meaningfulness, their usefulness is limited. Compared to univariate filters, the SG model yields better forecasting accuracy of output growth and inflation.

In contrast to recent literature, we find evidence that conditioning on our SG improves a univariate inflation forecast excluding a measure of economic slack.

Our results suggest that augmenting conventional multivariate models with sub-sector data offers a variety of advantages, with the only disadvantage being higher computational cost. We believe that our model provides a transparent narrative that is consistent with the data and helpful for the policy debate.

References

Baxter, M. and R. G. King (1999). Measuring business cycles: Approximate band-pass filters for economic time series. *Review of Economics and Statistics 81*(4), 575–593.

Blagrave, P., M. R. Garcia-Saltos, M. D. Laxton, and F. Zhang (2015). A simple multivariate filter for estimating potential output. *IMF Working Papers 79*.

Blanchard, O., E. Cerutti, and L. Summers (2015). Inflation and activity–two explorations and their monetary policy implications. Technical report, National Bureau of Economic Research.

Blanchard, O. J. and D. Quah (1989, September). The Dynamic Effects of Aggregate Demand and Supply Disturbances. *American Economic Review 79*(4), 655–673.

Chib, S. (1993). Bayes regression with autoregressive errors: A Gibbs sampling approach. *Journal of Econometrics 58*(3), 275–294.

Clark, P. K. (1987). The cyclical component of US economic activity. *Quarterly Journal of Economics 102*(4), 797–814.

Clark, T. E. and M. W. McCracken (2006). The predictive content of the output gap for inflation: Resolving in-sample and out-of-sample evidence. *Journal of Money, Credit and Banking 38*(5), 1127–1148.

Cochrane, J. H. (1994). Permanent and transitory components of GNP and stock prices. *Quarterly Journal of Economics 109*(1), 241–265.

Cogley, T., G. E. Primiceri, and T. J. Sargent (2010). Inflation-gap persistence in the US. *American Economic Journal: Macroeconomics 2*(1), 43–69.

Coibion, O. and Y. Gorodnichenko (2015). Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation. *American Economic Journal: Macroeconomics 7*(1), 197–232.

Coibion, O., Y. Gorodnichenko, and M. Ulate (2017). The cyclical sensitivity in estimates of potential output. Technical report, National Bureau of Economic Research.

Diebold, F. X. and R. S. Mariano (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics 13*(3), 253–263.

Doran, H. E. (1992). Constraining Kalman filter and smoothing estimates to satisfy time-varying restrictions. *Review of Economics and Statistics 74*(3), 568–572.

Dotsey, M., S. Fujita, and T. Stark (2017). Do Phillips curves conditionally help to forecast inflation? *International Journal of Central Banking 14*(4), 43–92.

Dupasquier, C., A. Guay, and P. St-Amant (1999). A survey of alternative methodologies for estimating potential output and the output gap. *Journal of Macroeconomics 21*(3), 577–595.

Durbin, J. and S. J. Koopman (2012). *Time series analysis by state space methods*. Oxford University Press.

Forbes, K., L. Kirkham, and K. Theodoridis (2021). A trendy approach to UK inflation dynamics. *The Manchester School 89*, 23–75.

Gerlach, S. (2017). The output-inflation trade-off in switzerland, 1916–2015. *CEPR Discussion Paper DP11714*.

Gerlach, S. and F. Smets (1999). Output gaps and monetary policy in the EMU area. *European Economic Review 43*(4-6), 801–812.

Gordon, R. J. (2014). The turtle's progress: Secular stagnation meets the headwinds. In *Secular stagnation: facts, causes and cures*, Volume 2014, pp. 47–60. CEPR Press London.

Guérin, P., L. Maurin, and M. Mohr (2015). Trend-cycle decomposition of output and euro area inflation forecasts: A real-time approach based on model combination. *Macroeconomic Dynamics 19*(2), 363–393.

Hamilton, J. D. (1994). *Time series analysis*, Volume 2. Princeton University Press.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics 100*(5), 831–843.

Hasenzagl, T., F. Pellegrino, L. Reichlin, and G. Ricco (2022). A model of the Fed's view on inflation. *Review of Economics and Statistics 104*(4), 686–704.

Havik, K., K. Mc Morrow, F. Orlandi, C. Planas, R. Raciborski, W. Röger, A. Rossi, A. Thum-Thysen, and V. Vandermeulen (2014). The production function methodology for calculating potential growth rates & output gaps. Technical report, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Hodrick, R. J. (2020). An exploration of trend-cycle decomposition methodologies in simulated data. Technical report, National Bureau of Economic Research.

Hodrick, R. J. and E. C. Prescott (1997). Postwar US business cycles: An empirical investigation. *Journal of Money, Credit, and Banking 29*(1), 1–16.

Jarociński, M. and M. Lenza (2018). An inflation-predicting measure of the output gap in the euro area. *Journal of Money, Credit and Banking 50*(6), 1189–1224.

Kamber, G., J. Morley, and B. Wong (2018). Intuitive and reliable estimates of the output gap from a Beveridge-Nelson filter. *Review of Economics and Statistics 100*(3), 550–566.

Kuttner, K. N. (1994). Estimating potential output as a latent variable. *Journal of Business & Economic Statistics 12*(3), 361–368.

Morley, J. C. (2007). The slow adjustment of aggregate consumption to permanent income. *Journal of Money, Credit and Banking 39*(2-3), 615–638.

Morley, J. C., C. R. Nelson, and E. Zivot (2003). Why are the Beveridge-Nelson and unobserved-components decompositions of GDP so different? *Review of Economics and Statistics 85*(2), 235–243.

Nelson, C. R. (2008). The Beveridge-Nelson decomposition in retrospect and prospect. *Journal of Econometrics 146*(2), 202–206.

Oh, K. H., E. Zivot, et al. (2006). The Clark model with correlated components. *University of Washington Working Paper*.

Okun, A. M. (1963). *Potential GNP: its measurement and significance*. Cowles Foundation for Research in Economics at Yale University.

Orphanides, A. and S. van Norden (2002). The unreliability of output-gap estimates in real time. *Review of Economics and Statistics 84*(4), 569–583.

Quast, J. and M. H. Wolters (2022). Reliable real-time output gap estimates based on a modified Hamilton filter. *Journal of Business & Economic Statistics 40*(1), 152–168.

Rich, G. (1997). Monetary targets as a policy rule: Lessons from the Swiss experience. *Journal of Monetary Economics 39*(1), 113–141.

Schleicher, C. et al. (2003). Structural time series models with common trends and common cycles. *University of British Columbia*.

Stock, J. H. and M. W. Watson (1999). Forecasting inflation. *Journal of Monetary Economics 44* (2), 293–335.

Stock, J. H. and M. W. Watson (2007). Why has US inflation become harder to forecast? *Journal of Money, Credit and Banking 39*, 3–33.

Stock, J. H. and M. W. Watson (2008). Phillips curve inflation forecasts. In *Understanding Inflation and the Implications for Monetary Policy: A Phillips Curve Retrospective*, pp. 101–186. MIT Press.

Streicher, S. (2022). RGAP: Output gap estimation in R. *KOF Working Papers 503*.

Stuart, R. (2018). A quarterly Phillips curve for Switzerland using interpolated data, 1963–2016. *Economic Modelling 70*, 78–86.

Summers, L. H. (2015). Demand side secular stagnation. *American Economic Review 105* (5), 60–65.

A Appendix

A.1 Decompositions

The decomposition of potential output growth and trend employment growth into its sector contributions directly follows by the aggregation constraints detailed in Section 2.2.

To facilitate the decomposition of the output gap into a weighted average of sector output gaps, we assume that relative previous period prices w_{it}^p for real potential output T_t are the same as for real output Y_t, i.e.,

$$T_t = \sum_i^n w_{it}^p T_{it}.$$

Hence,

$$\begin{aligned}
g_t &= \frac{Y_t}{T_t} - 1 \\
&= \frac{\sum_i^n w_{it}^p Y_{it}}{T_t} \frac{T_{it}}{T_{it}} - 1 \\
&= \sum_i^n w_{it}^p w_{it}^T \frac{Y_{it}}{T_{it}} - 1 \\
&= \sum_i^n w_{it}^p w_{it}^T \left(\frac{Y_{it}}{T_{it}} - 1 \right) + \sum_i^n w_{it}^p w_{it}^T - 1 \\
&= \sum_i^n w_{it}^p w_{it}^T g_{it},
\end{aligned}$$

where $w_{it}^T = {}^{T_{it}}/_{T_t}$ denotes relative potential output in sector i. The decomposition of the employment gap follows analogously.

A.2 Estimation algorithm

To estimate our model parameters and unobserved states, we adopt a Gibbs sampling procedure involving simulation smoothing based on Durbin and Koopman (2012) and related articles.

The parameter set $\Theta = \{\theta_j\}_j$ contains the subsets

$$\theta_\tau = \sigma_\tau^2, \qquad \theta_\mu = \sigma_\mu^2, \qquad \theta_g = \left\{\phi_1, \phi_2, \sigma_c^2\right\},$$

$$
\begin{aligned}
&\theta_{\tau_i} = \sigma^2_{\tau_i}, && \theta_{\mu_i} = \sigma^2_{\mu_i}, && \theta_{c_i} = \left\{\beta_i, \phi_{i1}, \phi_{i2}, \sigma^2_{ic}\right\}, \\
&\theta_{e\tau} = \sigma^2_{\tau_e}, && \theta_{e\mu} = \sigma^2_{\mu_e}, && \theta_{c^e} = \left\{\psi_{e0}, \psi_{e1}, \psi_{e2}, \phi_{e1}, \phi_{e2}, \sigma^2_{ec}\right\}, \\
&\theta_{e_i\tau} = \sigma^2_{\tau^e_i}, && \theta_{e_i\mu} = \sigma^2_{\mu^e_i}, && \theta_{c^e_i} = \left\{\psi_{e_i0}, \psi_{e_i1}, \psi_{e_i2}, \phi_{e_i1}, \phi_{e_i2}, \sigma^2_{e_ic}\right\}, \\
&\theta_{u\tau} = \sigma^2_{\tau_u}, && \theta_{u\mu} = \sigma^2_{\mu_u}, && \theta_{c_u} = \left\{\psi_{u0}, \psi_{u1}, \psi_{u2}, \phi_{u1}, \phi_{u2}, \sigma^2_{uc}\right\}, \\
&\theta_{\pi\tau} = \sigma^2_{\tau_\pi}, && && \theta_{c_\pi} = \left\{\psi_{\pi0}, \psi_{\pi1}, \psi_{\pi2}, , \phi_{\pi1}, \phi_{\pi2}, \sigma^2_{\pi c}\right\},
\end{aligned}
$$

where all trend parameters are listed in the left column, all drift coefficients in the middle column, and all cycle and loading parameters in the right column. Assuming a block independence structure, we have that

$$
p(\boldsymbol{\theta}) = \prod_{\theta_j \in \Theta} p(\theta_j),
$$

where $\boldsymbol{\theta}$ stacks all components of Θ. Thus, the distribution of the parameters factorizes into all trend, drift, and cycle and loading components, respectively.

A.2.1 Trends

For the local linear trends, the only two parameters are the trend and drift innovation variances σ^2_τ and σ^2_μ. For notational convenience, we drop the subscripts. We impose

$$
\pi\left(\sigma^2\right) = \mathcal{IG}\left(s_0, \nu_0\right)
$$

as prior distribution. For the trend $\boldsymbol{\tau} = \{\tau_t\}_t$, using standard results, we obtain

$$
p\left(\sigma^2 \middle| \boldsymbol{\tau}\right) = \prod_{t=3}^{T} p\left(\varepsilon_t \middle| \sigma^2\right) p\left(\sigma^2\right) \propto \mathcal{IG}\left(s_*, \nu_*\right)
$$

with

$$
\begin{aligned}
\nu_* &= \nu_0 + T, \\
s_* &= s_0 + \sum_{t=3}^{n} \varepsilon_t^2,
\end{aligned}
$$

where $\varepsilon_t = \varepsilon_{\tau t} = \Delta\tau_t - \mu_t$. For the drift, we replace $\boldsymbol{\tau}$ with $\boldsymbol{\mu} = \{\mu_t\}_t$ and set $\varepsilon_t = \varepsilon_{\mu t} = \Delta\mu_t$. For trend inflation, we assume a random walk without drift, for which the innovation term simplifies to $\varepsilon_t = \varepsilon_{\tau t} = \Delta\tau_t$.

A.2.2 Cycles and loadings

All of our observation equations are variations of a linear model with autoregressive errors, for which we apply the results of Chib (1993). Let now

$$y_t = \mathbf{x}_t'\boldsymbol{\beta} + \varepsilon_t, \quad \Phi(L)\,\varepsilon_t = u_t, \quad u_t \sim \mathcal{N}\left(0, \sigma^2\right),$$

where $\Phi(L) = 1 - \phi_1 L - \ldots - \phi_p L^p$, $\boldsymbol{\beta}$ is a $s \times 1$ vector of coefficients and $\mathbf{x_t}$ is a $s \times 1$ vector of covariates. Define

$$y_t^* = \Phi(L)\, y_t, \qquad \mathbf{x}_t^* = \Phi(L)\,\mathbf{x}_t,$$

for $t = p+1, \ldots, T$ and $\mathbf{y}^* = \{y_t^*\}_t, \mathbf{y} = \{y_t\}_t$ and $\mathbf{X}^* = \{\mathbf{x}^*\}_t$ are of dimension $T - p \times 1$ and $T - p \times s$, respectively.

We assume the prior distribution of the involved parameters factorizes, i.e.,

$$\pi\left(\boldsymbol{\beta}, \sigma^2, \boldsymbol{\phi}\right) = \pi(\boldsymbol{\beta})\,\pi\left(\sigma^2\right)\pi(\boldsymbol{\phi})$$

with $\boldsymbol{\phi} = (\phi_1, \ldots, \phi_p)'$ and for the individual prior distributions,

$$\begin{aligned}
\boldsymbol{\beta} &\sim \mathcal{N}_s\left(\boldsymbol{\beta}_0, \mathbf{A}_0^{-1}\right),\\
\sigma^2 &\sim \mathcal{IG}\left(\nu_0/2, \delta_0/2\right),\\
\boldsymbol{\phi} &\sim \mathcal{N}_p\left(\boldsymbol{\phi}_0, \boldsymbol{\Phi}_0^{-1}\right) I_{\phi\in S_\phi}.
\end{aligned}$$

The posterior distribution of the coefficient vector is given by

$$\begin{aligned}
\boldsymbol{\beta}|\mathbf{y} &\sim \mathcal{N}_s\left(\tilde{\boldsymbol{\beta}}_0, \tilde{\mathbf{A}}^{-1}\right),\\
\tilde{\mathbf{A}} &= \mathbf{A}_0 + \sigma^{-2}\mathbf{X}^{*\prime}\mathbf{X}^*,\\
\tilde{\boldsymbol{\beta}} &= \tilde{\mathbf{A}}^{-1}\left(\mathbf{A}_0\boldsymbol{\beta}_0 + \sigma^{-2}\mathbf{X}^*\mathbf{y}^*\right),
\end{aligned}$$

that of the variance by

$$\begin{aligned}
\sigma^2|\mathbf{y}, \boldsymbol{\beta}, \boldsymbol{\phi} &\sim \mathcal{IG}\left(\frac{T - p + \nu_0 + k}{2}, \frac{\delta_0 + d_\beta}{2}\right),\\
d_\beta &= \left(\mathbf{y}^* - \mathbf{X}^*\boldsymbol{\beta}\right)'\left(\mathbf{y}^* - \mathbf{X}^*\boldsymbol{\beta}\right),
\end{aligned}$$

and the autoregressive coefficient by

$$\boldsymbol{\phi}|\mathbf{y},\boldsymbol{\beta},\sigma^2 \sim \mathcal{N}_p\left(\tilde{\phi},\tilde{\boldsymbol{\Phi}}^{-1}\right) I_{\phi},$$
$$\tilde{\boldsymbol{\Phi}} = \boldsymbol{\Phi}_0 + \sigma^{-2}\mathbf{E}'\mathbf{E},$$
$$\tilde{\boldsymbol{\phi}} = \tilde{\boldsymbol{\Phi}}^{-1}\left(\boldsymbol{\Phi}_0\boldsymbol{\phi}_0 + \sigma^{-2}\mathbf{E}'\mathbf{E}\right).$$

where $\mathbf{E} = \{\boldsymbol{\varepsilon}_t\}_t, \boldsymbol{\varepsilon}_t = (\varepsilon_{t-1},\ldots,\varepsilon_{t-p})$ is a $T-p\times p$ matrix (Chib, 1993).

It is straightforward to see that each observation equation is a subgroup of this model. For instance, for the sector cycle equations we have $y_{it} - \tau_{it} = \beta_i g_t + c_{it}$ with $c_{it} = \phi_{i1}c_{it-1} + \phi_{i2}c_{it-2} + \varepsilon_{c_it}$, i.e., the above model is of dimension $s = 1$ and $p = 2$. In the case of the output gap, the covariate and coefficient vectors $\mathbf{x}_t$ and $\boldsymbol{\beta}$ are dropped.

A.2.3 Algorithm

The algorithm is structured in four blocks: The first three blocks sample the parameter vector $\boldsymbol{\theta}^k$ conditional on the states $\boldsymbol{\alpha}^{k-1}$ and the last block samples $\boldsymbol{\alpha}^k$ conditional on $\boldsymbol{\theta}^k$. More precisely, the first block deals with all trend equations in separate Gibbs steps. In the second block, the parameters of the equations involving loading factors and autoregressive cycles are drawn in another Gibbs step. The third block is an additional Gibbs step to draw the parameters of the output gap equation. The final block applies simulation smoothing as suggested by Durbin and Koopman (2012) conditional on the previously drawn parameters.

Initialization: We use the prior means to initialize all parameters $\boldsymbol{\theta}^0$ and apply the Kalman filter and smoother based on those parameters to initialize the states $\boldsymbol{\alpha}^0$.

Recursion: For $k = 1,\ldots,K$:

1. Trends (Gibbs steps): Draw all trend variances $\sigma^{2^k}|\tau^{k-1}$.

2. Sector output, aggregate and sector employment, unemployment and inflation (Gibbs steps): For each equation, draw autoregressive coefficients, loading coefficients, and

cycle variances, i.e.,

$$\begin{aligned} \boldsymbol{\phi}^k &\mid \sigma^{2^{k-1}}, \boldsymbol{\alpha}^{k-1} \\ \boldsymbol{\beta}^k &\mid \boldsymbol{\phi}^k, \sigma^{2^{k-1}}, \boldsymbol{\alpha}^{k-1} \\ \sigma^{2^k} &\mid \boldsymbol{\beta}^k, \boldsymbol{\phi}^k, \boldsymbol{\alpha}^{k-1} \end{aligned}$$

sequentially in this order as detailed in Section A.2.1. If the characteristic polynomial $\Phi^k(x)$ has roots inside the unit circle, redraw $\boldsymbol{\phi}^k$.

3. Output gap (Gibbs step): Draw autoregressive coefficients and cycle variance, i.e.,

$$\begin{aligned} \boldsymbol{\phi}^k &\mid \sigma^{2^{k-1}}, \boldsymbol{\alpha}^{k-1} \\ \sigma^{2^k} &\mid \boldsymbol{\phi}^k, \boldsymbol{\alpha}^{k-1} \end{aligned}$$

sequentially in this order as detailed in Section A.2.1, conditional on the trend τ^{k-1} and cycle g^{k-1}. If the characteristic polynomial $\Phi^k(x)$ has roots inside the unit circle, redraw $\boldsymbol{\phi}^k$.

4. States: Apply the simulation smoothing recursion (Durbin and Koopman, 2012) to sample the unobserved states conditional on the parameters

$$\boldsymbol{\alpha}^k \mid \boldsymbol{\theta}^k.$$

Discard the first K_b draws of $\left\{\boldsymbol{\theta}^k\right\}_k$ and $\{\boldsymbol{\alpha}\}_k$ and finally select each 10th draw from the remaining sample.

A.3 Robustness

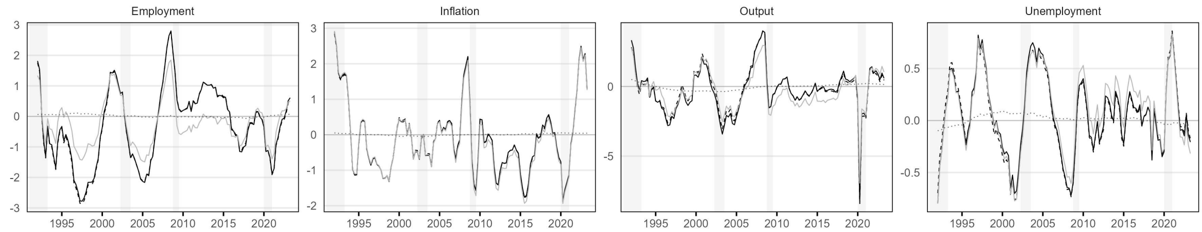
A.3.1 Number of production sectors

To assess the sensitivity of our model to the number of sectors, we split the 5 output and employment sectors into 8 and re-estimate our main model for Switzerland. The aggregate sector trade, transport and hospitality is split up into its three sub-components.[33]

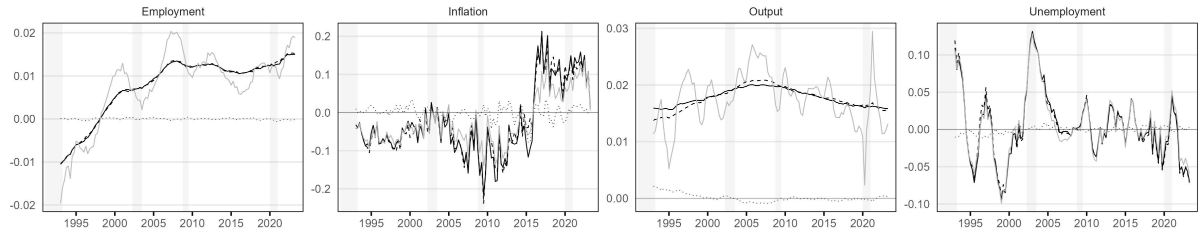
[33]The second component actually consists of transport and communication services.

In addition, financial and other economic services is dissected into financial services and the remaining economic services, the latter of which comprises real estate activities, professional, scientific, and technical services and finally administrative and support service activities. Figure A.1 compares the resulting latent series (dotted) to the main model (solid) and the baseline model without sectors (solid grey) and additionally features the differences between the main model and the version with more sectors (dashed). The differences are negligible, especially compared to those that prevail to the baseline model.

(a) Gap (in %)



(b) Trend growth (yoy in %)



(c) Drift (qoq in %)

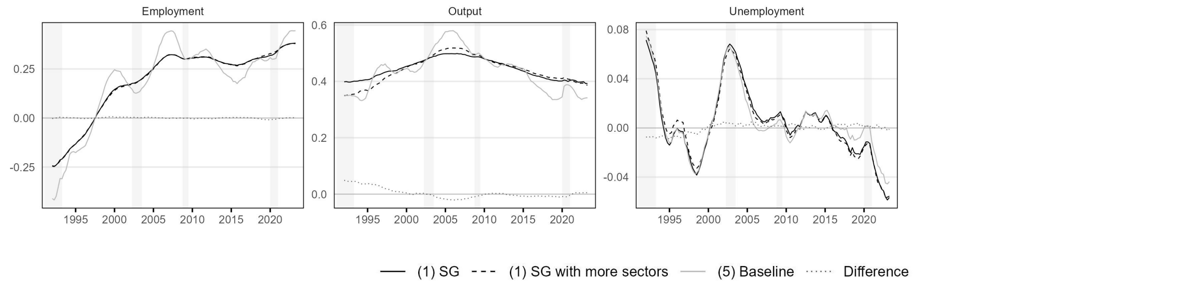


Figure A.1: Sensitivity to the number of sectors. The plots compare model (1) which includes 5 production and employment sectors to an alternative model with 8 sectors, and to the baseline model (5) without sectors. The dashed line defines the difference between the 5-sector and 8-sector model. Vertical shaded areas highlight recessions.

A.4 Figures

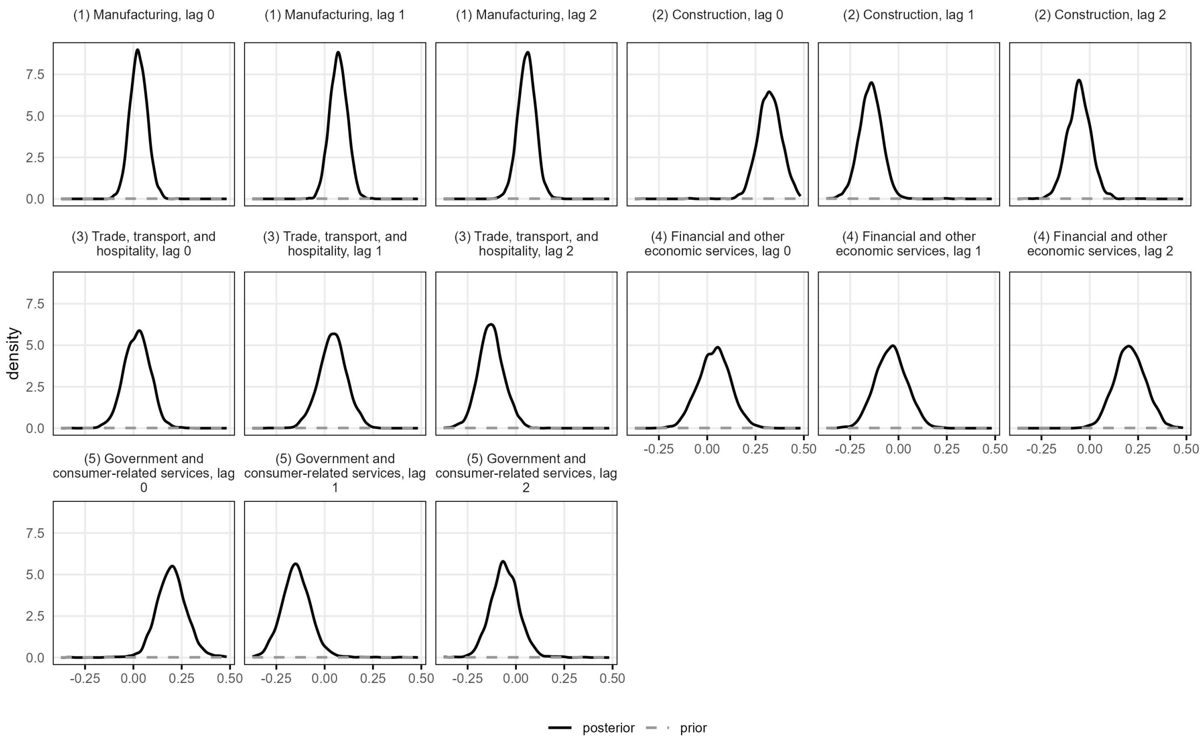
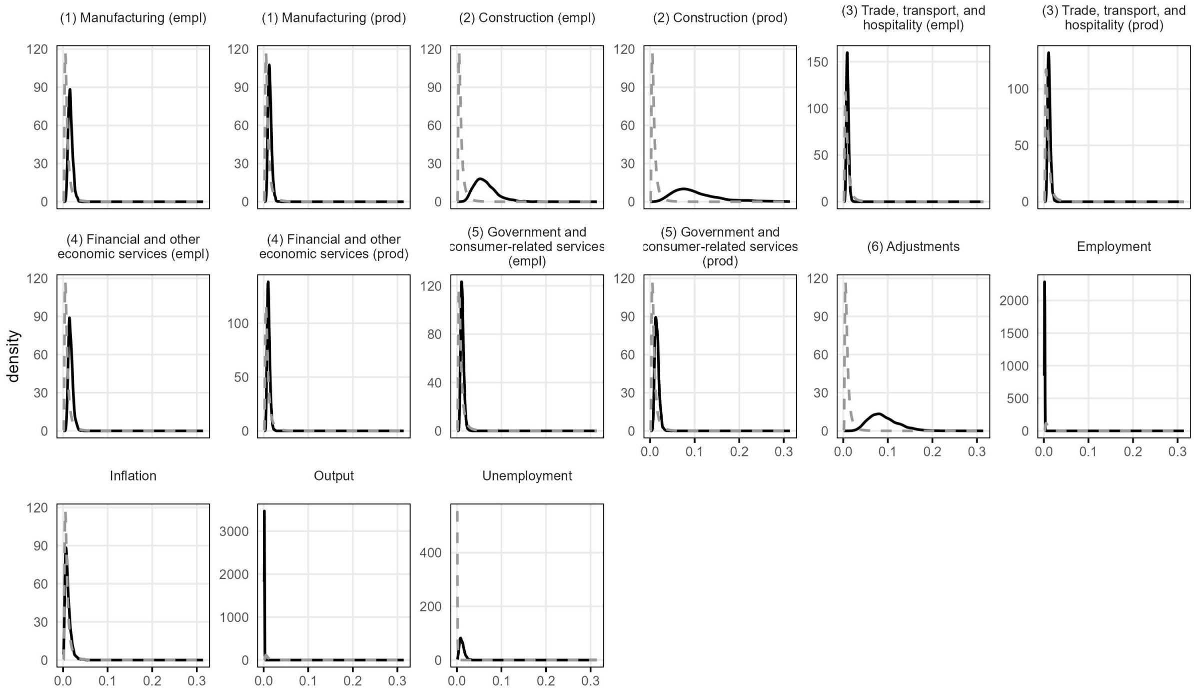
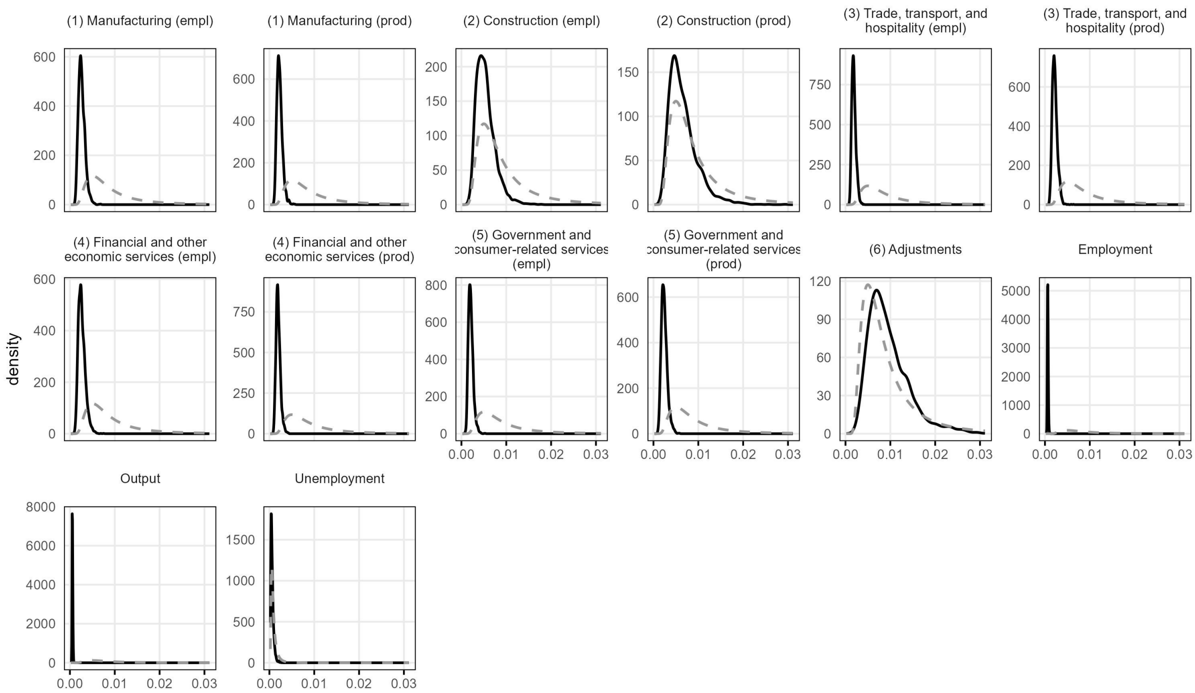


Figure A.2: Prior and posterior distribution of sector employment loadings on the output gap. The prior distributions are specified as in Table 1. The posterior densities are based on 50'000 draws, with the first 25'000 being discarded. Of the remaining draws, all but every 10th draw are discarded.

(a) Trend variances



(b) Trend drift variances



(c) Cycle variances

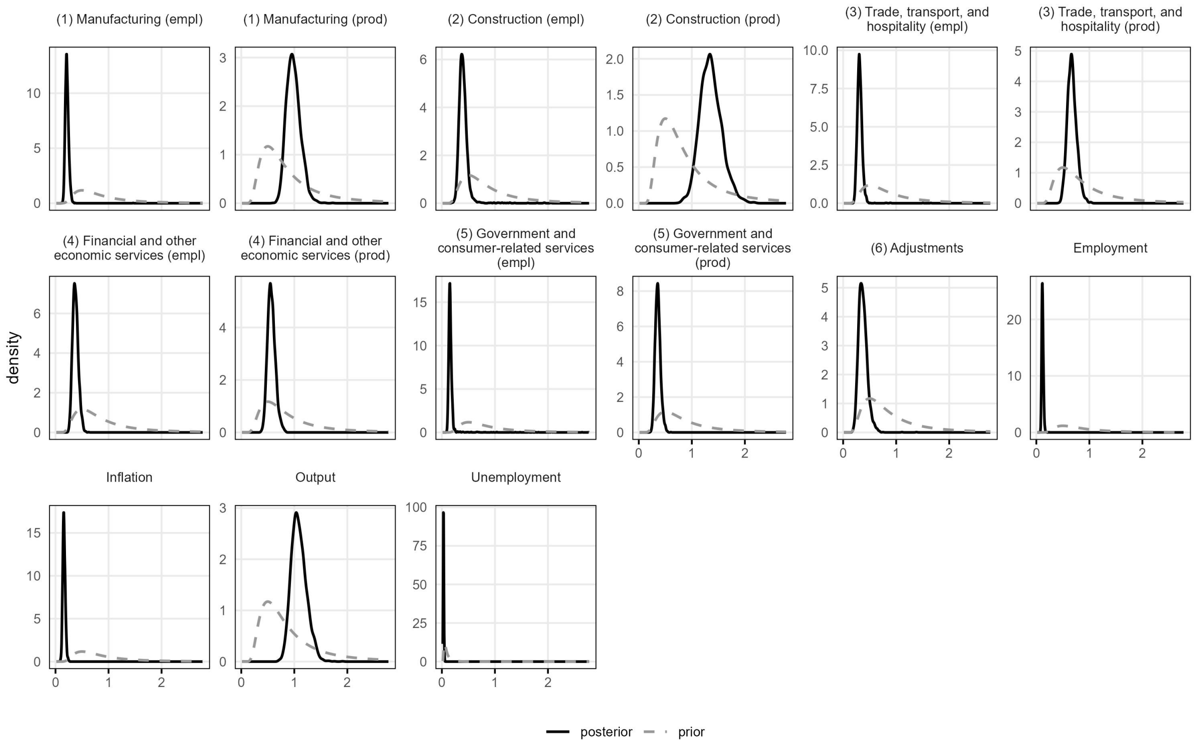
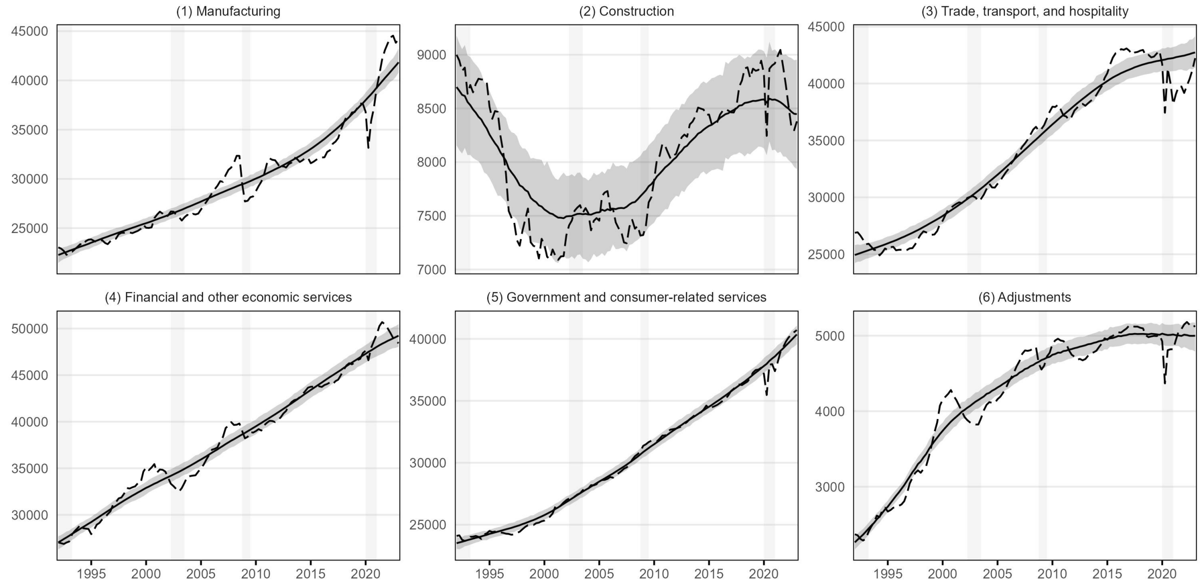


Figure A.3: Prior and posterior distribution of trend, drift, and cycle variances. The prior distributions are specified as in Table 1. The posterior densities are based on 50'000 draws, with the first 25'000 being discarded. Of the remaining draws, all but every 10th draw are discarded.

(a) Sector output trends



(b) Sector employment trends

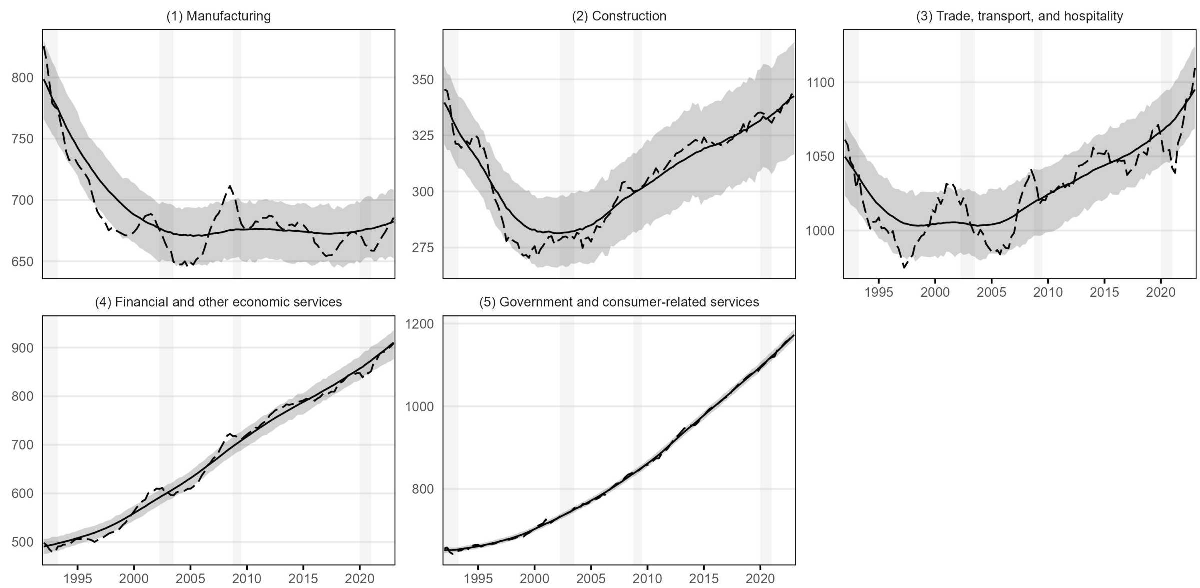
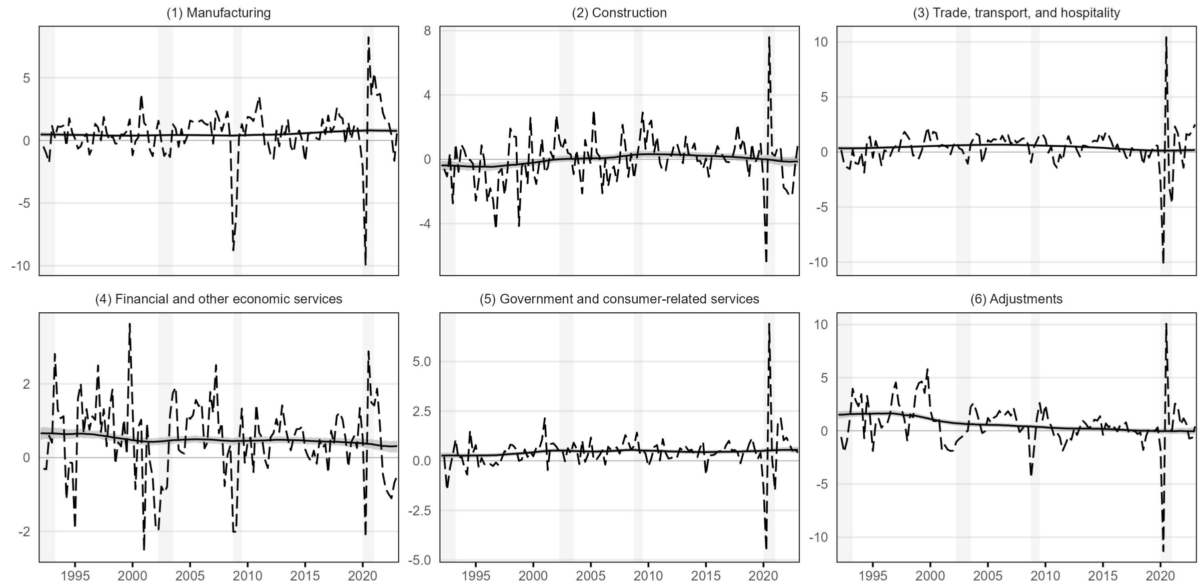


Figure A.4: Sector output and employment trends. Output in mio CHF (upper panel) and full-time equivalent employment in thousand (lower panel). The original data are dashed and the trends solid. The shaded areas indicate 68% HPDI. Vertical shaded areas highlight recessions.

(a) Sector output drifts



(b) Sector employment drifts

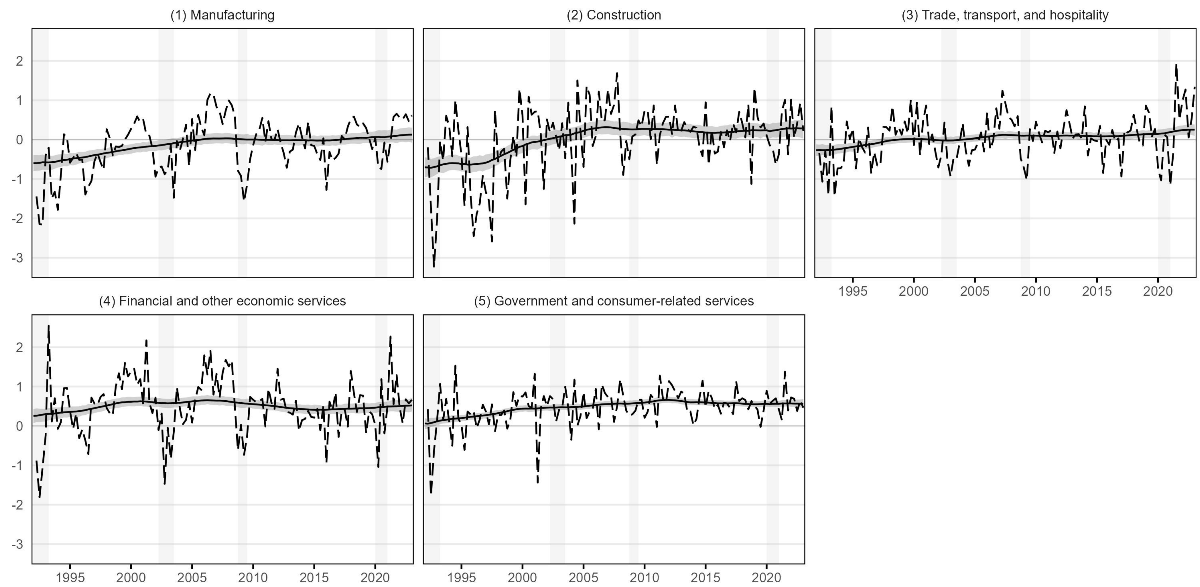
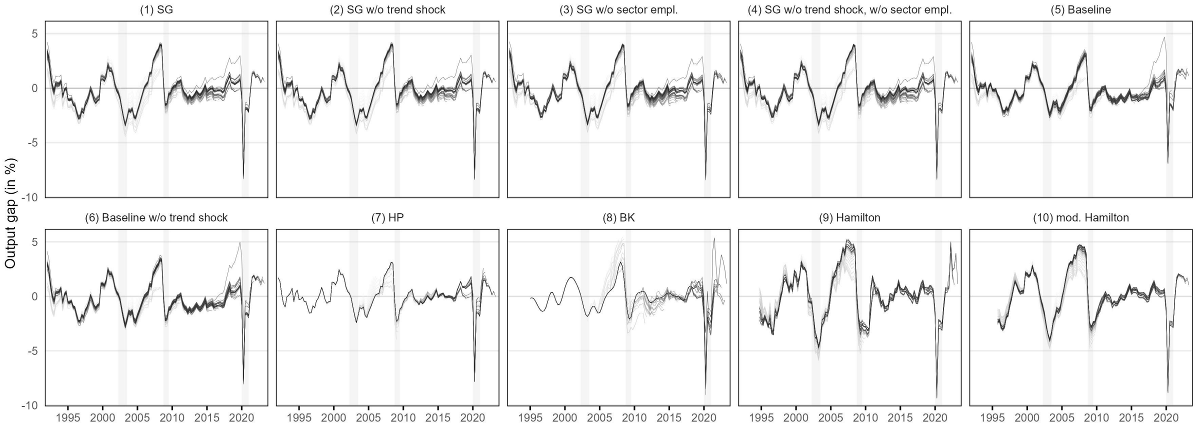


Figure A.5: Sector output and employment drifts. Output and employment growth in %. The original data are dashed and the trends solid. The shaded areas indicate 68% HPDI. Vertical shaded areas highlight recessions.

(a) Output gap (in %)



(b) Potential growth (yoy in %)

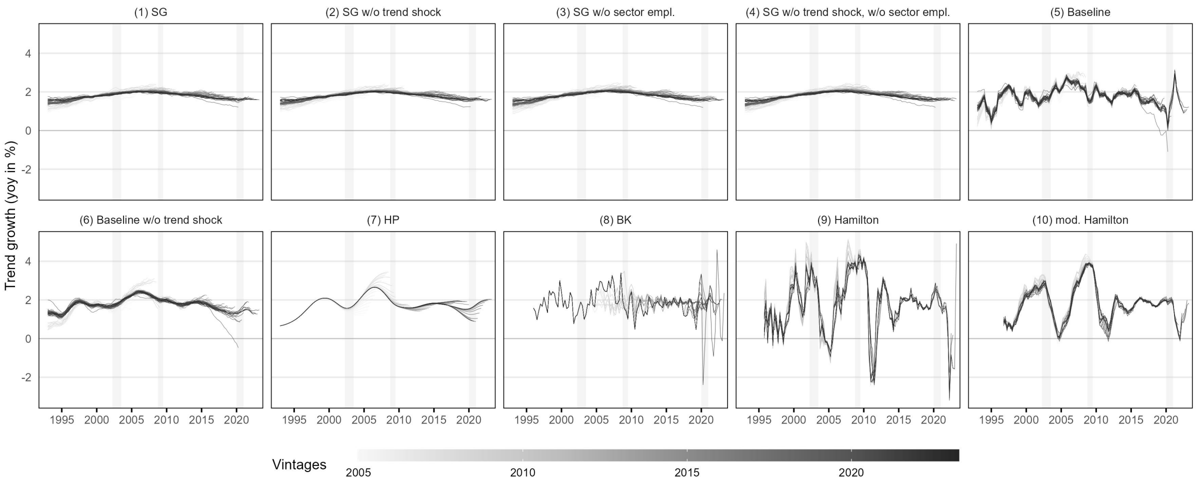


Figure A.6: Pseudo real-time estimates. Pseudo real-time estimates are computed for the vintages from 2005 Q1 until 2023 Q2 at quarterly frequency. Vertical shaded areas highlight recessions.

A.5 Tables

Table A.1. Gap correlations

	Output	(1)	(2)	(3)	(4)	(5)	(6)	Employment	Unemployment	Inflation	(sector) empl.	nom. weights
Output	1.00										0.60	1.00
(1) Manufacturing	0.74	1.00									0.39	0.22
(2) Construction	0.02	0.05	1.00								0.63	0.05
(3) Trade, transport, and hospitality	0.54	−0.03	0.06	1.00							0.47	0.25
(4) Financial and other economic services	0.54	0.38	−0.40	−0.10	1.00						0.27	0.26
(5) Government and consumer-related services	0.47	0.35	0.32	0.49	−0.31	1.00					0.21	0.19
(6) Adjustments	0.78	0.43	−0.23	0.40	0.63	0.20	1.00					0.03
Employment	0.60	0.37	0.02	0.49	0.14	0.51	0.40	1.00				
Unemployment	−0.67	−0.47	0.17	−0.43	−0.34	−0.32	−0.53	−0.75	1.00			
Inflation	0.57	0.60	0.10	0.22	0.10	0.46	0.39	0.29	−0.38	1.00		

Notes: Correlation coefficients between the output gap, sector output gaps, the employment and unemployment gap, the inflation gap and (sector) employment gaps. The weights reflect average nominal output weights over the sample period.

Table A.3. Revision and reliability indicators including the COVID-19 pandemic

	Final vintage		Revision				Initial vs. Final	
	Mean	SD	Mean	SD	RMSR	NRMSR	COR	SIGN
				Output gap (in %)				
(1) SG	−0.21	1.61	0.44	0.88	0.98	0.61	0.85	0.24
(2) SG w/o trend shock	−0.18	1.61	0.46	0.86	0.97	0.60	0.87	0.29
(3) SG w/o sector empl.	−0.22	1.58	0.53	0.90	1.04	0.66	0.84	0.26
(4) SG w/o trend shock, w/o sector empl.	−0.18	1.58	0.60	0.87	1.05	0.66	0.85	0.27
(5) Baseline	−0.27	1.34	0.05	0.93	0.93	0.69	0.74	0.11
(6) Baseline w/o trend shock	−0.25	1.49	0.09	1.05	1.05	0.70	0.75	0.11
(7) HP	−0.00	1.30	0.00	1.04	1.03	0.79	0.74	0.26
(8) BK	0.14	1.43	−0.03	1.71	1.70	1.18	0.63	0.33
(9) Hamilton	−0.00	2.38	0.37	1.07	1.13	0.47	0.90	0.11
(10) mod. Hamilton	0.06	2.13	0.38	0.90	0.97	0.46	0.92	0.17
				Trend growth (yoy in %)				
(1) SG	1.78	0.15	−0.11	0.16	0.19	1.30	0.68	0.00
(2) SG w/o trend shock	1.78	0.15	−0.11	0.16	0.20	1.30	0.67	0.00
(3) SG w/o sector empl.	1.78	0.16	−0.14	0.19	0.23	1.42	0.66	0.00
(4) SG w/o trend shock, w/o sector empl.	1.78	0.16	−0.13	0.17	0.21	1.32	0.69	0.00
(5) Baseline	1.75	0.47	−0.04	0.34	0.34	0.73	0.86	0.02
(6) Baseline w/o trend shock	1.75	0.31	−0.08	0.42	0.43	1.37	0.69	0.02
(7) HP	1.75	0.42	−0.02	0.52	0.52	1.23	0.44	0.00
(8) BK	1.76	0.88	−0.06	0.90	0.89	1.01	−0.27	0.03
(9) Hamilton	1.69	1.45	−0.11	0.69	0.69	0.48	0.90	0.05
(10) mod. Hamilton	1.76	0.86	−0.11	0.32	0.33	0.38	0.95	0.00

Notes: RMSR denotes the root mean squared revision and NRMSR the normalized RMSR, i.e., the ratio of RMSR to the standard deviation of the final estimate. COR denotes the correlation and SIGN the frequency of sign mismatches between real-time and final estimates. Pseudo real-time estimates are estimated from 2005 Q1 until 2021 Q2 at quarterly frequency and 2023 Q4 defines the final vintage.

Table A.4. GDP forecast evaluation: Average $\tilde{\beta}$ coefficients

	Horizon in quarters											
	1	2	3	4	5	6	7	8	9	10	11	12
(1) SG	−0.11	$-0.29^{\dagger}$	$-0.44^{\dagger}$	$-0.59^{\dagger}$	$-0.71^{\dagger}$	$-0.84^{\dagger}$	$-0.98^{\dagger}$	$-1.11^{\dagger}$	$-1.22^{\dagger}$	$-1.30^{\dagger}$	$-1.39^{\dagger}$	$-1.49^{\dagger}$
(2) SG w/o trend shock	−0.11	$-0.29^{\dagger}$	$-0.44^{\dagger}$	$-0.59^{\dagger}$	$-0.71^{\dagger}$	$-0.83^{\dagger}$	$-0.98^{\dagger}$	$-1.11^{\dagger}$	$-1.21^{\dagger}$	$-1.30^{\dagger}$	$-1.39^{\dagger}$	$-1.49^{\dagger}$
(3) SG w/o sector empl.	−0.12	$-0.29^{\dagger}$	$-0.45^{\dagger}$	$-0.60^{\dagger}$	$-0.72^{\dagger}$	$-0.85^{\dagger}$	$-0.99^{\dagger}$	$-1.13^{\dagger}$	$-1.23^{\dagger}$	$-1.32^{\dagger}$	$-1.41^{\dagger}$	$-1.51^{\dagger}$
(4) SG w/o trend shock, w/o sector empl.	−0.12	$-0.29^{\dagger}$	$-0.45^{\dagger}$	$-0.59^{\dagger}$	$-0.72^{\dagger}$	$-0.85^{\dagger}$	$-0.99^{\dagger}$	$-1.12^{\dagger}$	$-1.23^{\dagger}$	$-1.31^{\dagger}$	$-1.41^{\dagger}$	$-1.50^{\dagger}$
(5) Baseline	$-0.17^{\dagger}$	$-0.41^{\dagger}$	$-0.63^{\dagger}$	$-0.82^{\dagger}$	$-0.98^{\dagger}$	$-1.13^{\dagger}$	$-1.30^{\dagger}$	$-1.44^{\dagger}$	$-1.55^{\dagger}$	$-1.63^{\dagger}$	$-1.71^{\dagger}$	$-1.80^{\dagger}$
(6) Baseline w/o trend shock	$-0.16^{\dagger}$	$-0.38^{\dagger}$	$-0.58^{\dagger}$	$-0.76^{\dagger}$	$-0.90^{\dagger}$	$-1.04^{\dagger}$	$-1.20^{\dagger}$	$-1.33^{\dagger}$	$-1.43^{\dagger}$	$-1.50^{\dagger}$	$-1.58^{\dagger}$	$-1.66^{\dagger}$
(7) HP	$-0.17^{\dagger}$	$-0.43^{\dagger}$	$-0.67^{\dagger}$	$-0.88^{\dagger}$	$-1.04^{\dagger}$	$-1.19^{\dagger}$	$-1.37^{\dagger}$	$-1.52^{\dagger}$	$-1.62^{\dagger}$	$-1.70^{\dagger}$	$-1.78^{\dagger}$	$-1.88^{\dagger}$
(8) BK	−0.07	−0.26	−0.52	$-0.79^{\dagger}$	$-1.02^{\dagger}$	$-1.22^{\dagger}$	$-1.39^{\dagger}$	$-1.54^{\dagger}$	$-1.68^{\dagger}$	$-1.81^{\dagger}$	$-1.92^{\dagger}$	$-2.02^{\dagger}$
(9) Hamilton	0.01	−0.01	−0.05	−0.08	−0.11	−0.16	−0.23	−0.30	$-0.36^{\dagger}$	$-0.43^{\dagger}$	$-0.49^{\dagger}$	$-0.57^{\dagger}$
(10) mod. Hamilton	0.02	−0.02	−0.07	−0.13	−0.20	−0.27	−0.36	$-0.44^{\dagger}$	$-0.52^{\dagger}$	$-0.59^{\dagger}$	$-0.68^{\dagger}$	$-0.78^{\dagger}$

Notes: † signals a rejection frequency of the null hypothesis of $\tilde{\beta} = 0$ at the 10% level of larger or equal 90%. Pseudo real-time estimates are estimated for vintages from 2005 Q1 until 2019 Q4 at quarterly frequency.

Table A.5. GDP forecast evaluation including the COVID-19 pandemic: Relative RMSE of model (1) SG to alternative models

	Horizon in quarters											
	1	2	3	4	5	6	7	8	9	10	11	12
	Equation (8a): $p = 0$											
(2) SG w/o trend shock	0.999	0.998	0.999	1.000	0.998	0.997	1.003	1.005	1.005	1.002	1.002	1.007*
(3) SG w/o sector empl.	1.003	1.003	1.006	1.007	1.001	1.000	0.998	0.992	0.991	0.991	0.984	0.978
(4) SG w/o trend shock, w/o sector empl.	1.001	1.003	1.004	1.005	1.001	0.996	0.996	0.990	0.990	0.987	0.979	0.971
(5) Baseline	0.981	0.965	0.966	0.964	0.954	0.950	0.958	0.948	0.963	0.977	0.989	1.003
(6) Baseline w/o trend shock	0.983	0.966	0.965	0.960	0.949	0.944	0.949	0.945	0.964	0.983	0.996	1.020
(7) HP	0.973	0.948	0.907**	0.888*	0.879*	0.861*	0.833*	0.831	0.832	0.827	0.820	0.813
(8) BK	0.946	1.006	0.974	0.938	0.907	0.870	0.824*	0.776	0.727	0.671	0.637	0.614
(9) Hamilton	0.958	0.960	0.960	0.940	0.918	0.906	0.903	0.916	0.941	0.959	0.968	0.968
(10) mod. Hamilton	0.956	0.963	0.959	0.939	0.920	0.907	0.905	0.914	0.932	0.941	0.939	0.926
	Equation (8b): $p = 0$, including Δg_t											
(2) SG w/o trend shock	0.999	0.997	0.998	1.000	0.999	0.996	1.003	1.004	1.003	1.000	0.999	1.001
(3) SG w/o sector empl.	1.006	1.002	1.006	1.006	1.001	0.997	0.996	0.991	0.989	0.989	0.983	0.979
(4) SG w/o trend shock, w/o sector empl.	1.004	0.998	1.000	0.999	0.997	0.991	0.993	0.989	0.989	0.989	0.981	0.973
(5) Baseline	0.979	0.946	0.951	0.957	0.952	0.956	0.964	0.955	0.972	0.985	0.994	0.990
(6) Baseline w/o trend shock	1.006	0.973	0.963	0.959	0.954	0.953	0.956	0.954	0.967	0.986	0.994	0.991
(7) HP	1.004	0.995	0.974	0.957	0.956	0.958	0.941	0.912	0.917	0.910	0.907	0.898
(8) BK	0.731	0.711	0.735	0.804*	0.816**	0.817**	0.800*	0.767	0.714	0.672	0.663	0.637
(9) Hamilton	1.042	0.994	0.986	0.963	0.945	0.937	0.932*	0.923*	0.937***	0.956	0.944	0.925
(10) mod. Hamilton	0.944	0.948	0.940	0.906	0.898	0.893	0.881	0.890	0.891	0.888	0.866	0.866
	Equation (8c): $p < 12$ chosen by BIC											
(2) SG w/o trend shock	0.999	0.998	0.998	0.999	0.996	0.991	1.001	1.007	1.007	0.997	0.994	1.000
(3) SG w/o sector empl.	1.003	1.003	1.006	1.028	1.024	1.016	1.006	0.979	1.002	0.980	0.987	0.978
(4) SG w/o trend shock, w/o sector empl.	1.001	1.003	1.002	1.038	1.032	1.019	1.007	0.978	1.005	0.983	0.989	0.970
(5) Baseline	0.981	0.965	0.955	0.997	0.996	1.008	1.015	1.018	1.016	0.992	0.978	0.945
(6) Baseline w/o trend shock	0.983	0.966	0.972	0.981	0.977	0.972	0.979	0.976	0.986	0.980	0.963	0.948
(7) HP	0.973	0.949	0.976	1.117	1.139	1.114	1.140**	1.049	1.065	0.998	0.965	0.899
(8) BK	0.612	0.126	0.021	0.030	0.032	0.044	0.053	0.049	0.122**	0.086	0.108**	0.115***
(9) Hamilton	0.958	0.960	0.890*	1.066	1.074	1.089	1.083	1.085	1.093	1.078	1.079	1.038
(10) mod. Hamilton	0.956	0.963	0.873*	1.019	1.052	1.098	1.110	1.150	1.132	1.109	1.057	1.013

Notes: *, **, and *** denote significant differences in forecasting accuracy at the 10, 5, and 1% level based on a two-sided Diebold and Mariano (1995) with squared loss. Pseudo real-time estimates are estimated for vintages from 2005 Q1 until 2023 Q2 at quarterly frequency.

Table A.6. Inflation forecast evaluation including the COVID-19 pandemic: Relative RMSE of model (1) SG to alternative models

	Horizon in quarters											
	1	2	3	4	5	6	7	8	9	10	11	12
	Equation (9a): h period ahead y-o-y inflation ($\pi_{t+h} = P_{t+h} - P_{t+h-4}$)											
(2) SG w/o trend shock	0.999	0.998	0.998	0.997	0.998	0.997	0.998	0.995	0.996	0.999	0.999	1.002
(3) SG w/o sector empl.	1.000	1.000	1.001	1.003	1.003	1.002	1.003	1.003	1.001	0.996	0.987	0.981
(4) SG w/o trend shock, w/o sector empl.	1.000	1.000	1.001	1.001	1.000	0.999	0.997	0.999	0.998	0.994	0.984	0.980
(5) Baseline	0.998	0.998	0.999	0.996	0.990	0.984	0.965	0.965	1.041	0.966	0.963	0.964
(6) Baseline w/o trend shock	1.000	1.001	1.001	0.997	0.988	0.981	0.965	0.964	0.972	0.972	0.958	0.952
(7) HP	1.001	1.002	0.994	0.980	0.963	0.959*	0.966**	0.954***	0.975	0.949	0.893	0.858*
(8) BK	0.981	0.952	0.599	0.093**	0.052	0.111***	0.072**	0.106***	0.090***	0.096***	0.105***	0.090**
(9) Hamilton	0.998	0.995	0.885*	0.909	0.881*	0.904	0.919	0.953	1.033	0.970	0.885	0.949
(10) mod. Hamilton	1.003	0.975	0.961	0.966	0.827**	0.858*	0.874	0.925	0.982	0.965	0.893	0.914
Only infl.	1.002	1.008	1.014	1.003	0.992	0.972**	0.957	0.937*	0.994	0.988	0.960	0.949
	Equation (9a): h period ahead q-o-q inflation ($\pi_{t+h} = P_{t+h} - P_{t+h-1}$)											
(2) SG w/o trend shock	0.998*	0.999	0.998	0.999	0.998	0.995**	0.994	0.994	0.995*	1.000	1.000	1.000
(3) SG w/o sector empl.	1.001	1.001	1.004	1.004	1.003	1.009	1.006	1.003	1.003	1.009	1.012	1.006
(4) SG w/o trend shock, w/o sector empl.	1.001	1.002	1.001	1.001	0.999	1.000	1.002	0.999	1.004	1.006	1.001	1.003
(5) Baseline	0.998	0.995	0.996	0.991	0.983	0.974	0.961	0.940	0.959	0.988	0.970	0.974
(6) Baseline w/o trend shock	0.998	0.996	0.995	0.987	0.979	0.968	0.965	0.947	0.962	0.985	0.970	0.965
(7) HP	0.984	0.952	0.970	0.962	0.958*	0.939*	0.940**	0.951	0.936***	0.933**	0.930*	0.937*
(8) BK	0.966	0.943	0.915	0.908	0.952	1.000	1.005	1.018	1.018	0.977	0.981	0.986
(9) Hamilton	0.976	0.993	0.988	0.967	0.963	0.967	0.965	1.002	0.972	0.964	0.934	0.936
(10) mod. Hamilton	0.959	0.938	0.978	0.972	0.959	0.940	0.953	0.945	0.962	0.986	0.935	0.926
Only infl.	0.984	0.943	0.911	0.966	0.942	0.905***	0.857***	0.859*	0.878**	0.886***	0.852***	0.908**
	Equation (9b): h period inflation ($\bar{\pi}_{t+h} = \ln P_{t+h} - \ln P_t$)											
(2) SG w/o trend shock	1.001	0.999	0.998	0.998	0.998	0.999	0.999	0.999	0.999	0.998	0.998	0.999
(3) SG w/o sector empl.	1.004	1.005	1.006	1.008	1.009	1.007	1.005	1.003	1.002	0.996	0.993	0.985***
(4) SG w/o trend shock, w/o sector empl.	1.004	1.005	1.005	1.007	1.008	1.008	1.006	1.003	1.001	0.995	0.992	0.983***
(5) Baseline	0.999	1.004	1.008	1.009	1.007	1.004	1.001	0.997	0.994	0.920	0.976	0.974
(6) Baseline w/o trend shock	1.005	1.010	1.014	1.014	1.012	1.008	1.004	0.998	0.995	0.921	0.977	0.974
(7) HP	1.005	1.011	1.007	1.003	1.003	1.005	1.008	1.012	1.015	0.939	0.990	0.987
(8) BK	0.959*	0.951	0.951	0.970	0.999	1.023*	1.035**	1.044	1.045	0.962	0.945	0.942
(9) Hamilton	0.969	0.985	1.002	1.014	1.016	1.020	1.020	1.017	1.014	0.939	0.928	0.935
(10) mod. Hamilton	0.967	0.982	1.000	1.012	1.015	1.019	1.018	1.012	1.009	0.935	0.924	0.928
Only infl.	0.987	0.970	0.948	0.926	0.911	0.881	0.849*	0.816**	0.793**	0.721***	0.703***	0.695***

Notes: *, **, and *** denote significant differences in forecasting accuracy at the 10, 5, and 1% level based on a two-sided Diebold and Mariano (1995) with squared loss. Pseudo real-time estimates are estimated for vintages from 2005 Q1 until 2023 Q2 at quarterly frequency.

Table A.2. Posterior distributions

	Cycle variance				Trend variance				Trend drift variance			
	Mean	Median	D_1	D_9	Mean	Median	D_1	D_9	Mean	Median	D_1	D_9
Output	1.0821	1.0687	0.9119	1.2743	0.0016	0.0015	0.0012	0.0020	0.0006	0.0006	0.0005	0.0007
(1) Manufacturing	0.9847	0.9729	0.8239	1.1574	0.0138	0.0133	0.0092	0.0192	0.0023	0.0022	0.0016	0.0031
(2) Construction	1.3558	1.3439	1.1094	1.6159	0.1060	0.0922	0.0496	0.1759	0.0068	0.0060	0.0034	0.0109
(3) Trade, transport, and hospitality	0.6728	0.6666	0.5633	0.7917	0.0117	0.0113	0.0080	0.0160	0.0022	0.0021	0.0015	0.0030
(4) Financial and other economic services	0.5687	0.5618	0.4810	0.6639	0.0111	0.0106	0.0074	0.0153	0.0020	0.0019	0.0014	0.0026
(5) Government and consumer-related services	0.3599	0.3566	0.2999	0.4238	0.0153	0.0147	0.0100	0.0213	0.0024	0.0023	0.0017	0.0033
(6) Adjustments	0.6290	0.3656	0.2814	0.4763	0.0902	0.0852	0.0521	0.1345	0.0097	0.0085	0.0048	0.0158
Employment	0.1175	0.1156	0.0986	0.1374	0.0018	0.0018	0.0014	0.0023	0.0006	0.0006	0.0005	0.0008
(1) Empl. Manufacturing	0.2167	0.2129	0.1789	0.2589	0.0167	0.0159	0.0110	0.0233	0.0027	0.0025	0.0018	0.0036
(2) Empl. Construction	0.4611	0.3890	0.3161	0.4893	0.0638	0.0595	0.0353	0.0970	0.0053	0.0050	0.0031	0.0080
(3) Empl. Trade, transport, and hospitality	0.3216	0.3088	0.2594	0.3701	0.0098	0.0094	0.0067	0.0134	0.0019	0.0018	0.0013	0.0025
(4) Empl. Financial and other economic services	0.3764	0.3712	0.3105	0.4492	0.0170	0.0162	0.0112	0.0236	0.0026	0.0025	0.0018	0.0036
(5) Empl. Government and consumer-related services	0.3281	0.1537	0.1264	0.1951	0.0122	0.0118	0.0082	0.0168	0.0021	0.0020	0.0015	0.0027
Unemployment	0.0306	0.0303	0.0223	0.0391	0.0116	0.0108	0.0054	0.0190	0.0006	0.0005	0.0003	0.0011
Inflation	0.1600	0.1581	0.1314	0.1911	0.0105	0.0087	0.0043	0.0189				

	Loading on output gap				Loading on output gap, lag 1				Loading on output gap, lag 2			
	Mean	Median	D_1	D_9	Mean	Median	D_1	D_9	Mean	Median	D_1	D_9
(1) Manufacturing	1.3772	1.3759	1.2760	1.4800								
(2) Construction	0.8550	0.8549	0.7242	0.9868								
(3) Trade, transport, and hospitality	1.4679	1.4696	1.3897	1.5466								
(4) Financial and other economic services	0.5319	0.5313	0.4558	0.6064								
(5) Government and consumer-related services	0.6641	0.6640	0.5958	0.7330								
(6) Adjustments	1.5904	1.5910	1.5282	1.6530								
Employment	0.1496	0.1488	0.1103	0.1896	0.0898	0.0894	0.0475	0.1315	0.0530	0.0533	0.0118	0.0941
Unemployment	−0.0538	−0.0539	−0.0770	−0.0301	−0.0758	−0.0761	−0.0995	−0.0520	−0.0415	−0.0418	−0.0668	−0.0161
Inflation	0.1765	0.1766	0.1291	0.2247	0.0815	0.0820	0.0283	0.1335	0.0495	0.0496	0.0010	0.0971

	Loading on sector gap				Loading on sector gap, lag 1				Loading on sector gap, lag 2			
	Mean	Median	D_1	D_9	Mean	Median	D_1	D_9	Mean	Median	D_1	D_9
(1) Empl. Manufacturing	0.0265	0.0261	−0.0299	0.0830	0.0723	0.0721	0.0143	0.1302	0.0545	0.0549	−0.0029	0.1124
(2) Empl. Construction	0.3249	0.3236	0.2459	0.4043	−0.1440	−0.1432	−0.2187	−0.0685	−0.0561	−0.0560	−0.1311	0.0191
(3) Empl. Trade, transport, and hospitality	0.0186	0.0198	−0.0656	0.1035	0.0434	0.0444	−0.0472	0.1321	−0.1294	−0.1302	−0.2118	−0.0459
(4) Empl. Financial and other economic services	0.0362	0.0372	−0.0686	0.1397	−0.0375	−0.0359	−0.1395	0.0645	0.2086	0.2089	0.1053	0.3107
(5) Empl. Government and consumer−related services	0.1984	0.1969	0.1028	0.2984	−0.1485	−0.1503	−0.2469	−0.0535	−0.0615	−0.0585	−0.1516	0.0349

Notes: Mean, median, and first and ninth decile D_1 and D_9 of the posterior distribution.

KOF

ETH Zurich
KOF Swiss Economic Institute
LEE G 116
Leonhardstrasse 21
8092 Zurich, Switzerland

Phone +41 44 632 42 39
kof@kof.ethz.ch
www.kof.ch

© KOF Swiss Economic Institute